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Contact Point Estimation along Air Tube Based on Acoustic Sensing of Pneumatic System Noise

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***Abstract*— Active acoustic sensing is being widely used in various fields, with applications including shape estimation of soft pneumatic actuators. In a pneumatic system, air tubes are frequently adopted, and thus it is essential to detect failures along the air path. Although acoustic sensing has been used for detecting contact and identifying the contact position along a tube, it has not been applied to pneumatic systems. We devised an acoustic sensing method to this end for air tubes in a pneumatic system. As pneumatic system noise propagates through the air tube, we employed this type of noise instead of the conventional method of using a sound source or emitting vibration with an additional oscillator. We conducted several experiments that confirm the feasibility of the proposed method, succeeding to estimate the contact point on a 16 m air tube.**

I. Introduction

Recently, soft pneumatic actuators (SPAs) have been widely adopted as fingers in robotic hands [1] to safely and delicately grasp soft objects (e.g., fruits). Such systems are controlled using air pressure, and their configuration consists of an air compressor (or pump) and air tubes, besides the SPA itself. However, these actuators present some problems regarding management. When an air tube is entangled to the joints of a robot, the actuator does not work correctly, and the system must be timely recovered by detecting the tube contact position to prevent malfunction or damage.

Generally, contact sensors are used for determining the contact position in robot skins, but no suitable sensor is available for the air tube surface. Therefore, we propose contact point detection and estimation using the pneumatic system noise emitted from the pump of a pneumatic system, as illustrated in Figure 1. In previous works, active acoustic sensing has been used for contact position estimation. Unlike this approach, we leverage the propagated pneumatic noise as sensing variable, omitting the necessity of an additional sound source.

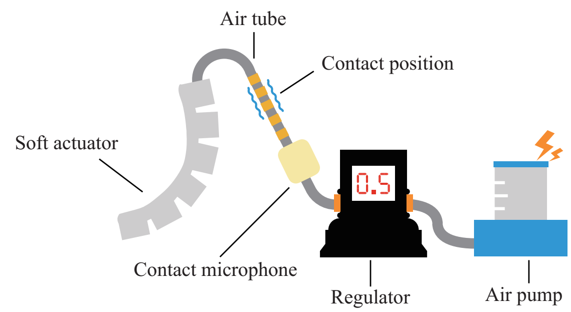

Fig. 1. Diagram of sensing technique for contact point estimation of tube air in pneumatic system

The rest of this paper is organized as follows. Section II describes related work and our contribution. Section III explains the acoustic sensing for contact point estimation, and Section IV reports the results of evaluation experiments and presents a discussion. Applications of the method to a robotic gripper and a user interface are presented in Section V. Finally, we draw conclusions and provide directions of future work in Section VI.

II. Related work

A. Acoustic sensing

Passive and active acoustic sensing for recognizing human activity and gestures has been actively studied in human–computer interaction. In these applications, passive acoustic sensing uses sounds generated from events related to human movements. For instance, Harrison et al. [2] proposed Scratch Input to recognize scratch patterns using the sound produced when a fingernail scrapes the surface of an object. Additionally, touch interaction has been enhanced by distinguishing tapping styles, such as using the finger or fingernail, based on acoustic sensing [3][4]. However, passive acoustic sensing requires a sufficient force or movement to generate a detectable sound, limiting its applicability.

In contrast, active acoustic sensing relies on a sound source, and thus it can be applied to interactions in which a detectable sound is not generated from unreliable sources. For instance, Ono et al. [5] proposed a method for detecting touch by attaching a piezoelectric speaker

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and a microphone to an object. The contact force is determined by analyzing the acoustic spectral response of the object [6]. Additionally, active acoustic sensing has been used in wearable devices for sensing human information such as joint angles [7], contact force [8], and gripping force [9]. Recently, active acoustic sensing has been used in SPA, as described in the following section.

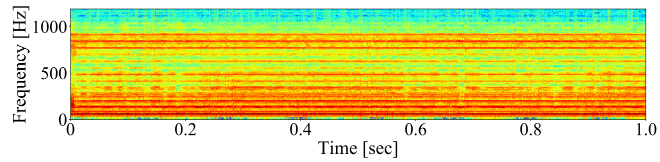
B. Active acoustic sensing for SPAs

SPAs are very popular because they provide an alternative to rigid actuation. When a robotic gripper is constructed using several SPAs, for example, an object can be grasped without damaging it [10]. Various sensing techniques for SPAs have been proposed, and the corresponding sensors should be flexible and easy to install. For instance, Zöller et al. [11] developed a soft pneumatic actuator which a microphone is installed in, and the contact location has been estimated. The method is categorized in passive acoustic sensing because an oscillator is not required as a sound source. On the other hand, the active acoustic sensing is also used for a soft pneumatic actuator. Takaki et al. [12] proposed a method to measure the actuator length based on active acoustic sensing. This method fulfills some requirements of sensors for SPAs, and we believe that active acoustic sensing is suitable for such actuators.

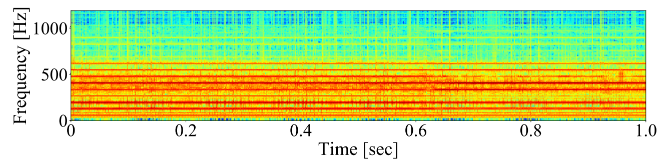
An SPA needs tubes for feeding air to its structures, and thus sensing should include the tubes. In fact, a tube entangled in a robot joint should be detected as soon as possible for correction. Contact sensing for tubes has been proposed using air pressure waves [13] and ultrasonic waves [14]. Likewise, Tejada et al. [15] proposed a method for contact position estimation based on active acoustic sensing. Although these methods have enabled contact sensing on the tube surface via active acoustic sensing, they have not been implemented in pneumatic systems. We noticed that a pneumatic system produces stationary noise. Therefore, we propose a method for contact position detection and estimation along a tube by leveraging the pneumatic system noise. Using this noise omits the necessity of an oscillator, which is usually employed for active acoustic sensing, thus notably simplifying the system configuration.

In summary, the contributions of this paper are follows.

- The key idea is to employ pneumatic noise instead of an emitter, such as an ultrasonic transducer and a speaker, for contact-position estimation, allowing for the air path to be reserved for the SPA.
- The contact position is estimated by data-driven approach using a convolutional neural networks instead of a theoretical physics model.
- A soft gripper controller based on our proposed method was implemented for indicating the feasibility of user interfaces for soft robotics.



(a) Pneumatic system noise



(b) Pneumatic noise

Fig. 2. Spectrogram of pneumatic system noise

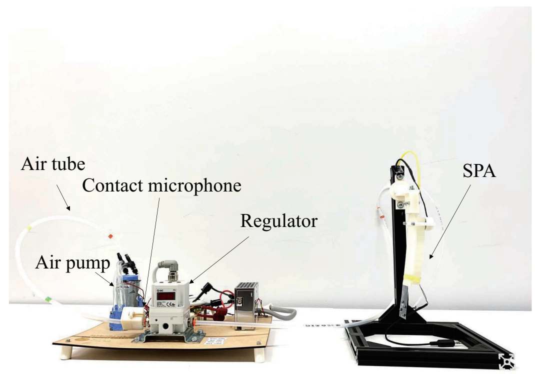


Fig. 3. Hardware configuration of the pneumatic system

III. Methodology

A. Pneumatic noise

Pneumatic systems have pumps that emit noise while feeding air to the tubes. We use this pneumatic noise for contact point estimation instead of an additional sound source for active acoustic sensing. Thus, the system configuration is simplified in comparison with active acoustic sensing based on a speaker. When the pump is activated, pneumatic system noise is generated, and given that the air tube is split by intermediate equipment, a contact microphone can be integrated into the system. Figure 2(a) shows the spectrogram of pneumatic noise, which occurs on the frequency band up to about 900 Hz. When the contact microphone is close to the pump, the acquired signal includes pneumatic and system noise, which together we call pneumatic system noise. In contrast, noise has a spectrum up to 600 Hz when the contact microphone is located after the system regulator as shown in Figure 2(b), and we call it pneumatic noise.

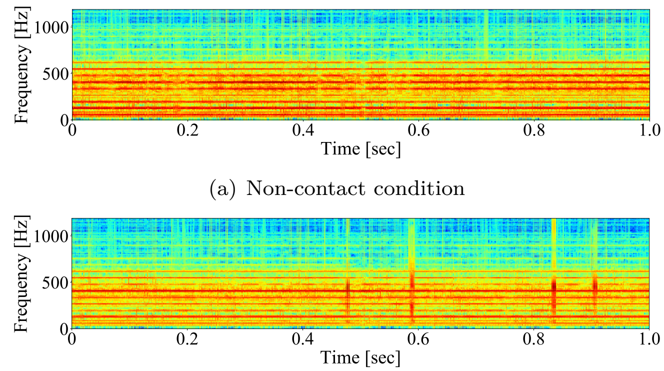
B. System configuration

The overall system configuration is shown in Figure 3. The pneumatic system consists of a pump (BTC IIS; Parker Hannifin, Hollis, NH, USA), a regulator (ITV1000; SMC, Tokyo, JP), air tubes (TIA07-100;

SMC, Tokyo, JP), and Pneu-Nets [16] as silicon SPA. The employed tube is made of nylon, and the inner and outer diameters of the tube are 4.57 and 6.35 mm, respectively. The tube is relatively hard for inserting the air pressure, and is therefore not deformed by touch; the putative contact is of low pressure. Additionally, the sensing device consists of a contact microphone (CM-01B, TE Connectivity, Schaffhausen, CH) to acquire the pneumatic system noise acting as a sound source. The estimation method is proposed for a general pneumatic system, which includes soft robotics. Therefore, the air path has to be reserved without oppilating the terminate of a tube, and the contact microphone is fixed to the surface of the air tube with a 3D-printed attachment, and the interference of environmental sounds is mitigated by employing the contact microphone. A digital-to-analog converter (Analog Discovery 2; Digilent, Pullman, WA, USA) is used to acquire the pneumatic system noise at sampling frequency 44.1 kHz, and the propagated noise is analyzed for contact point estimation.

C. Contact point estimation along air tube

When the air tube is touched or pressed by a hand or an object, the propagated pneumatic system noise changes its characteristics. We amplify the acquired noise by 40 dB and calculate the amplitude spectrum using the short-time Fourier transform (STFT) to obtain a spectrogram with frameshift length of 50 ms. Figure 4 shows spectrograms generated under two conditions, namely, with and without contact between the regulator and SPA. The amplitude spectrum of the propagated pneumatic system noise notably changes with contact, and thus the spectrogram can be used to extract features for contact estimation. We generate spectrograms within 1000 ms for training and estimation, and they are considered as image data of 300×20 pixels. These data are used as input for classification using a convolutional neural network (CNN) designed based on the VGG16 architecture [17]. The VGG16 network mainly consists of 5 max-pooling layers and 13 convolutional layers followed by 3 fully connected layers. Aiming to shorten the training time, we use a smaller architecture mainly consisting of 2 max-pooling layers and 4 convolutional layers followed by 3 fully connected layers, as shown in Figure 5. In a pneumatic system, air pressure varies to control the SPA, and thus we consider the influence of changing air pressure. Figure 6 shows the spectrogram obtained while varying the air pressure. A striped pattern appears lightly on the timing of increasing air pressure. As the spectrum amplitude varies with the increase in air pressure, we trained the CNN under different air pressures. For illustration purposes, we defined three contact points for classification and estimation of segments as being red, yellow, and green from the closer to the farther contact position along the tube. After training, the identification label was indicated on the display correctly when the contact point was touched, as



(a) Non-contact condition

(b) Contact condition

Fig. 4. Spectrograms from pneumatic noise with and without contact to air tube

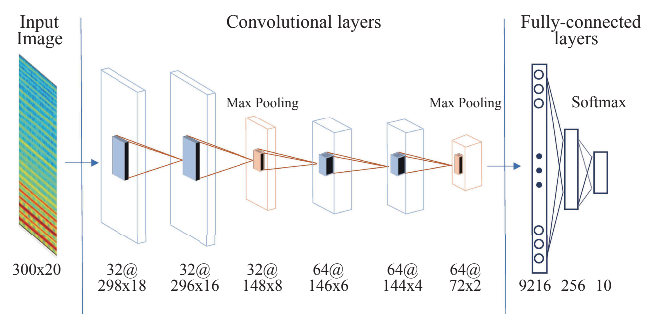


Fig. 5. Architecture of convolutional neural networks for classification

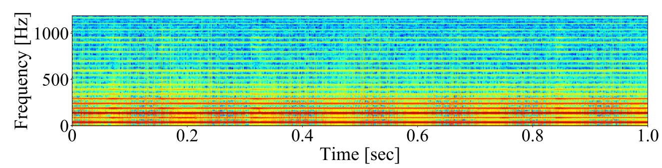


Fig. 6. Spectrogram from pneumatic noise under continuous variation of air pressure

shown in Figure 7. The spectrogram can be generated continuously, and the estimation rate is 20 Hz. The estimation was executed under changing air pressure conditions, the air pressure was varied from 0 to 62.1 kPa. The contact location can be accurately estimated even under changing air pressure.

IV. Evaluation experiments

A. Contact point estimation on split air tube

As mentioned above, the pneumatic system for this study consists of a SPA, a regulator, and a pump. The air path is split by the regulator, and thus the recognition rates were evaluated in the experimental conditions (a) and (b), as shown in Figure 8. In the experimental condition (a), the contact microphone is located on the air tube which connects to the pump. On the other hand, the contact microphone is attached to the air tube which connects to the soft pneumatic actuator in the experimental condition (b). The length

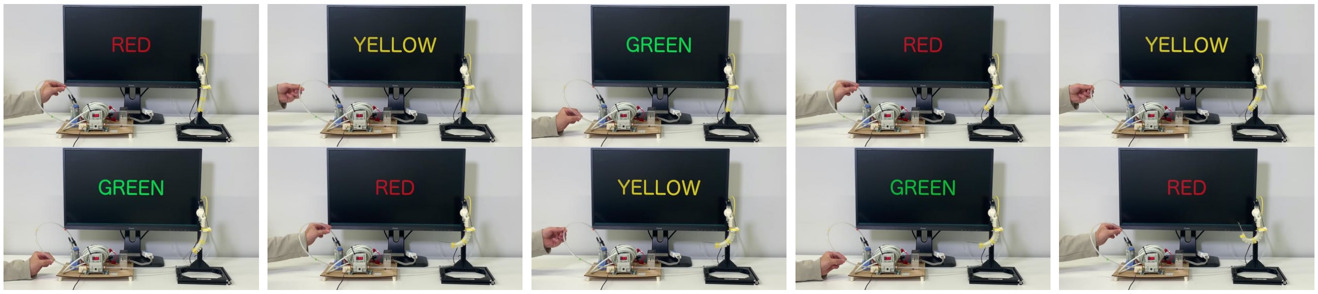


Fig. 7. Snapshots of contact point estimation in air tube

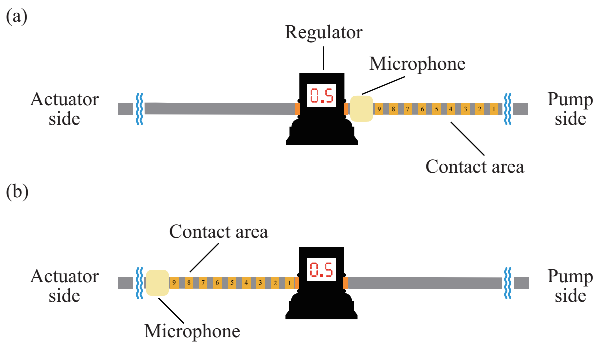
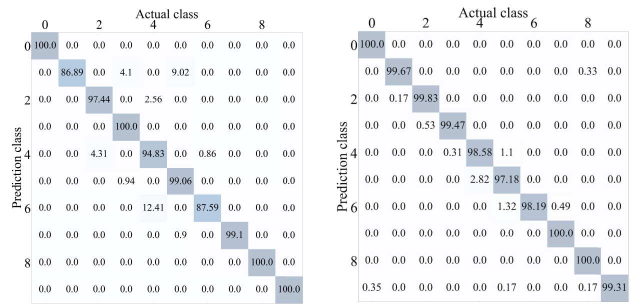


Fig. 8. Experimental conditions for evaluating different sensor locations



(a) Pump – Regulator (b) Regulator – SPA

Fig. 9. Confusion matrices of contact estimation for two measurement areas

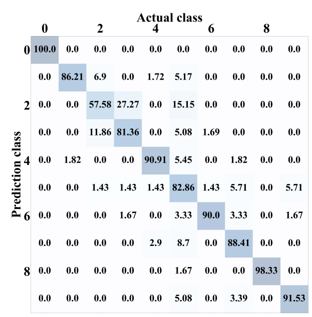


Fig. 10. Confusion matrix of contact estimation using neural networks

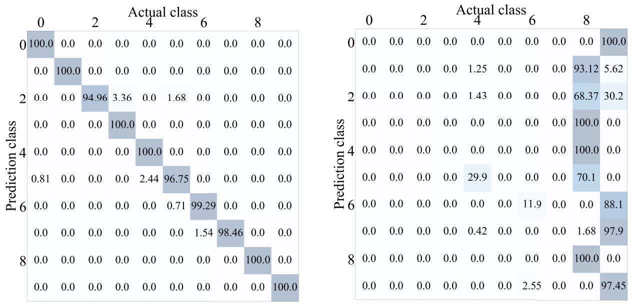
of each air tube is 500 mm. Numbers 1–9 indicate equal contact position segments along the tube starting from the pump, and number 0 indicates no contact. Data were recorded for each condition defined by the identification numbers over 31 seconds per condition. Moreover, we varied the air pressure while recording the data for robust contact point estimation. After recording the data, 600 spectrograms were obtained per contact point and the non-contact condition as input data for the CNN. We employed fivefold cross-validation for evaluation. Figure 9 shows the recognition rate for each class using confusion matrices for air tubes before and after the regulator. The mean recognition rates were approximately 97% in both tube positions. Hence, we confirmed that the recognition rate is not affected by the regulator. If we apply the proposed method to the failure detection of a pneumatic system, the method can detect the contact points on the whole air tube.

B. Features and machine-learning techniques for estimation

CNN is well-known as a powerful tool for classification, and we employed the CNN-based estimation for indicating a high recognition rate. However, a trade-off exists between the recognition rates and number of datasets, and annotation work is relatively difficult to apply in a CNN-based approach. Therefore, we tried to estimate the contact position using neural networks (NN) as a simple machine-learning technique. The experimental condition and dataset are similar to those described in Section IV-A and presented in Figure 9(b). The spectrogram is used as a 2D feature to input in the proposed method. The power spectrum is used as a 1D feature for the NN. Figure 10 shows the recognition rate of 10 classes, and the average of the recognition rate is 86.4%, which is lower than that of CNN; however, we confirmed the feasibility of using NN. Therefore, we can select a machine-learning technique for the estimation, depending on applications.

C. Evaluation of varying air pressure

We further evaluated the tolerance of estimation to varying air pressure. In this experiment, we attached the contact microphone to the air tube connected to the SPA. The identification of contact points as well as data acquisition was the same as the condition of Figure



(a) Various air pressures for training (b) One air pressure for training

Fig. 11. Confusion matrices of contact estimation for varying air pressure

9(a) from the experiment mentioned in Section IV-A. We increased the air pressure from 0 to 41.3 kPa at intervals of 10.3 kPa during data collection. Then, 600 spectrograms were obtained per contact condition.

Again, we evaluated the recognition rate by fivefold cross-validation, obtaining the confusion matrix shown in Figure 11(a). The recognition rate is around 99%, confirming that the proposed estimation is accurate under various air pressures. In contrast, Figure 11(b) shows the recognition rate when the CNN was trained with data at 0 kPa to classify data at 41.3 kPa for comparison. The mean recognition rate is around 20%, and the contact point is not identified correctly. Therefore, the proposed method trained with data at varying air pressure provides robust classification.

D. Evaluation of air tube length

After verifying the feasibility of the proposed estimation method for different sensor locations and several air pressures, we evaluated its performance according to the air tube length. Specifically, we changed the length between the regulator and SPA at 5 m increments and obtained the corresponding recognition rates at contact positions of 500 mm intervals. The air tube length from the pump to the regulator was 500 mm, and the contact microphone was attached to the air tube located next to the SPA. In addition, we fixed the air pressure to 10.3 kPa. Again, data collection and evaluation were performed as in the previous experiments.

Figure 12 shows the recognition rate per evaluated length, confirming no drop in estimation accuracy. As the longest air tube available was 16 m as shown in Figure 13, the recognition rate for this tube length is also indicated. The mean recognition rates are approximately 98% in all lengths, confirming that pneumatic noise is suitably propagated through long air tubes for accurate contact estimation. The dominant frequency in the pneumatic noise is distributed in a low-frequency band under 600 Hz, and thus the vibration can be propagated on long distances.

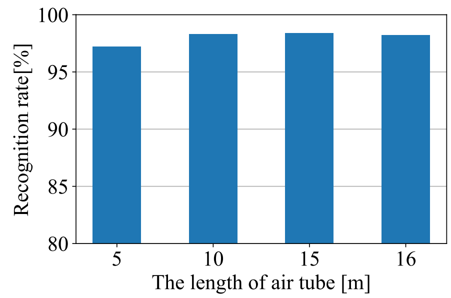


Fig. 12. Recognition rates of contact estimation for several air tube lengths

Fig. 13. Photograph of experiment using 16 m air tube

E. Evaluation of contact position resolution

In our current implementation, we employed a classifier to estimate contact points at distinguishable intervals of 500 mm. Although this resolution is suitable for detecting an error in a pneumatic system, the proposed method may be used in various applications such as user interfaces and contact sensing with shock absorber. Considering the requirements for these applications, we evaluated higher resolution of 25 mm and calculated the recognition rate on a 500 mm air tube. Data collection and evaluation were the same as those in the previous experiments, with air pressure being fixed at 10.3 kPa.

Figure 14 shows the recognition rate for this experiment using confusion matrices. The mean recognition rates for resolution of 25 mm is approximately 93%, showing an accuracy reduction for the 25 mm resolution. Still, the recognition rate remains above 90%, confirming the ability of the proposed method to handle a high density of contact points.

We employed a CNN classifier for estimating contact points given the difficulty to formulate analytical solutions based on pneumatic system noise as a sound source. Therefore, we required to collect a large dataset for CNN training and label the acquired

V. Robotic gripper based on SPA and user interface via air tube

SPAs are being increasingly adopted in various areas, such as robotic grippers and user interfaces. We implemented a robotic gripper featuring the proposed method. Three Pneu-Nets [16] were integrated using

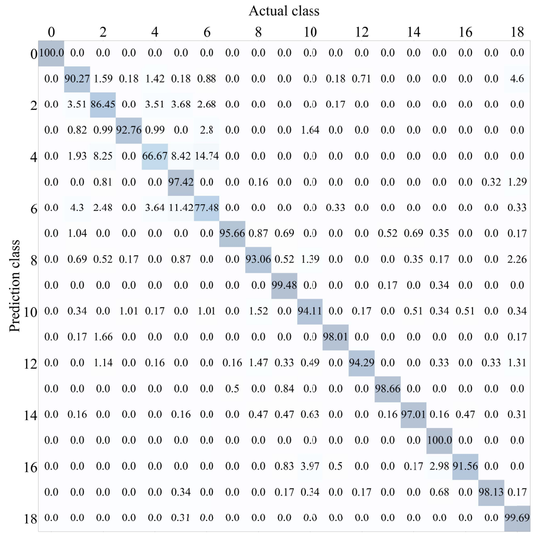
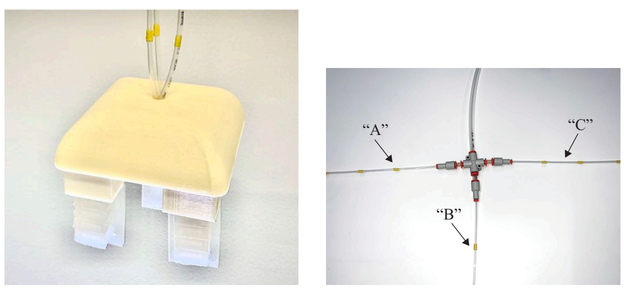


Fig. 14. Confusion matrices of estimation for short intervals between distinguishable contact points



(a) Soft pneumatic gripper (b) Air paths for fingers

Fig. 15. Robotic gripper constructed using three Pneu-Nets

a 3D-printed attachment (Mojo; Stratasys, Commerce Way, MN, USA) for constructing the robotic gripper, as shown in Figure 15. Additionally, the air paths are split for feeding air to all the fingers simultaneously.

A. Evaluation of multiple air channels

Although we conducted various experiments for confirming the feasibility of the proposed method, we did not evaluate the use of multiple air channels. For the gripper, we evaluated the recognition rate at each air path. In the robotic gripper, the length of each air path is 500 mm. We set contact points in intervals of 50 mm and attached a single contact microphone to the air tube before splitting. Data collection was conducted as in the previous experiments, obtaining 600 data segments per path. Figure 16 shows the recognition rates using confusion matrices for paths A, B, and C, which are 96%, 94%, and 95%, respectively. Thus, we confirmed that the proposed method is accurate for a pneumatic system with multiple air channels.

B. Robotic gripper operation using air tube contact

An application of the proposed method is detecting failure in a pneumatic system. In addition, user interfaces can be achieved based on tube contact. Thus, we implemented a user interface to control the robotic gripper to illustrate the proposed method. Contact point estimation was used for touch sensing on the interface to control the opening and closing of the gripper. We prepared six grasping objects such as "masking tape", "box cutter", "flathead screwdriver", "remote controller", "wallet", and "squeaky hammer". The maximum weight of the grasp objects is 245 g. In the current implementation, the air is fed when the contact is detected on the air tube. Figure 17 shows snapshots of this gripper control example, which was successfully executed.

VI. Discussion and limitation

A. Measurable length of air tube

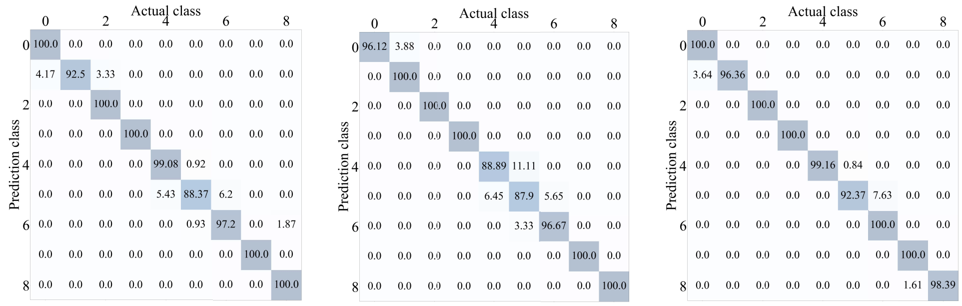
The frequency of pneumatic noise is lower than that of ultrasonic sound, and the attenuation of the propagated vibration is low when the pneumatic noise is used for sensing. Therefore, the proposed method would especially work well for a long air tube. In the experiment, the contact position was estimated using a 16-m air tube. Although the length is not a limitation, we confirmed high performance of the method when using a long tube.

B. Annotation work for training data

We employed a CNN classifier for estimating contact points, given the difficulty in formulating analytical solutions based on pneumatic system noise as a sound source. This requires a large dataset for CNN training and labeling of the acquired data; this process is time-consuming, and represents a limitation of the proposed method. Nevertheless, labeling of data obtained through pneumatic system noise is less burdensome than that for image-based object recognition, in which the labelling includes the manual data entry of segmented area. Therefore, we believe that automatic data collection of pneumatic system noise can be achieved using a robotic system. A robotics system can systematically obtain labelled data from different contact points by using actuators, thus replacing the manual contact for data collection adopted in this study.

C. System configuration

The system configuration includes a pneumatic pump without an air tank, and the implementation of a user interface via the air tube. Pneumatic noise was created continuously in our system, with uninterrupted estimation. In contrast, if the system is built using an intermediate air tank or a CO_2 cylinder, the pneumatic noise will be reduced. Figure 18 shows the spectrograms with and without contact with the tube, when the CO_2 cylinder is used instead of the pump. As expected, pneumatic noise was not observed, and thus, the system does not function as an active sensing scheme. However, the vibration generated by contact could be observed clearly. Therefore, it might be used for passive contact sensing. Our current implementation is limited in the sense that



(a) "A" (b) "B" (c) "C"

Fig. 16. Confusion matrices for contact estimation on every path

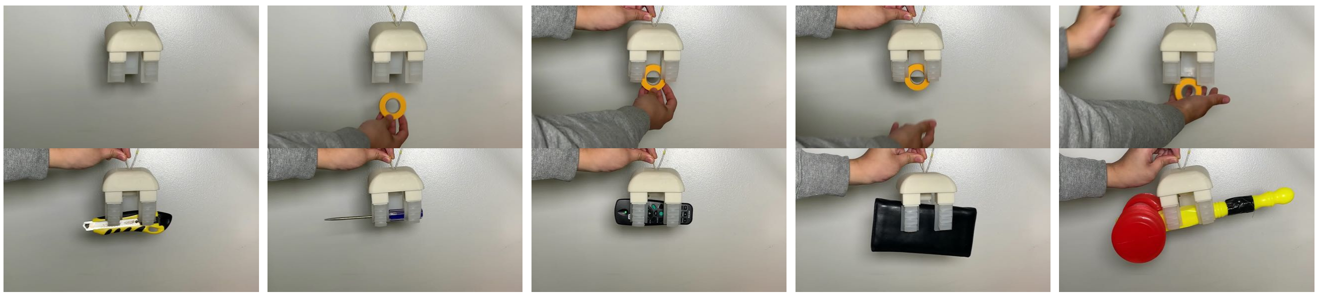
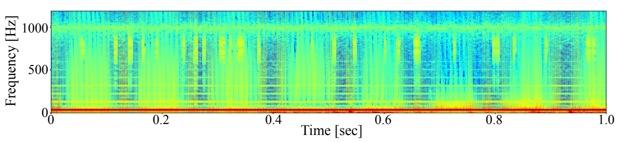
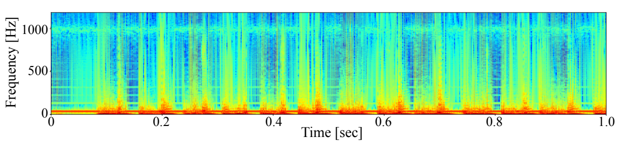


Fig. 17. Snapshots of robotic gripper control by touching air tube



(a) Non-contact condition



(b) Contact condition

Fig. 18. Spectrograms with and without contact to air tube when CO_2 cylinder is employed instead of the pump

a system configuration must be selected based on the application. However, it is possible to spread the system applicability by integrating active and passive sensing.

Additionally, we considered the use of a pneumatic valve because it can be used for actively controlling the actuator. The microphone can be adjusted to any location on the tube, and the optimal position where the pneumatic noise can be received can be selected. Therefore, we confirmed that the method works without any problems when a pneumatic valve is implemented onto our system.

D. Material and size of the air tube

The soft tube is not always more suitable than the hard tube because the vibration propagation on hard material is greater. Additionally, we confirmed that the proposed method does not work when the tube is too small. Tejada et al. [15] reported that a large tube is more suitable than a small tube but their reasoning was completely different from ours. In their method that functions according to shape-changing, the sound is propagated inside the tube. However, the pneumatic noise is propagated mainly on the surface of the tube, and the variance of the propagated vibration depends on the contact area.

E. Applications

The contact-point estimation can be used to detect failures according to an obstruction in pneumatic systems. The proposed method can be widely applied to general pneumatic systems, and the estimation could detect instances of air leaks. Additionally, we implemented the user interfaces via the air tube for the robotic gripper, and confirmed the method's high potential in soft robotics. In our implementation, it is not necessary to change the system configuration, and the sensor attachment to the tube surface is optional. Therefore, the method is versatile and has a wide-spread applicability.

VII. Conclusion

We propose a method for estimation of contact point position along an air tube using pneumatic system noise. We evaluated the feasibility of the proposed method under varying experimental conditions including sensor position, air pressure, and air tube length. Also when we used the 16 m air tube as the longest tube, we could confirm that the recognition rate of estimating contact position was approximately 98%. Moreover, we implemented a robotic gripper using three Pneu-Nets actuators as fingers, confirming that the proposed method provides accurate contact point estimation in a pneumatic system with various air paths. As acquiring and labeling the dataset for CNN training were time-consuming tasks in this study, we will consider a robotic system for automated data collection and labeling as future work.

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