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Wearable Band-shaped Device and Detection Algorithm for Laryngeal Elevation in Mendelsohn Maneuver

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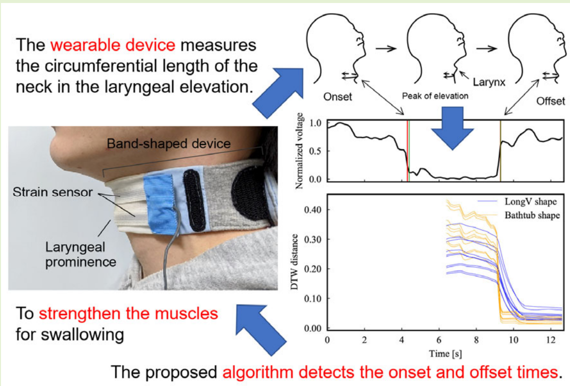
***Abstract*—** **Aspiration pneumonia is a serious condition in the elderly. To strengthen the muscles required for swallowing, patients can train using the Mendelsohn maneuver, wherein they maintain their larynx at the top of the laryngeal elevation during swallowing. This study describes a wearable device to detect the onset and offset times of the laryngeal elevation for a biofeedback system to support this training. The biofeedback system consists of a band-shaped device with stretchable strain sensors. The strain sensors measure the change of circumferential length of the neck. An algorithm detects the onset and offset times of the laryngeal elevation based on the absolute first-order difference of the measured data and distance between the measured data and template data by pattern matching. The algorithm detected the onset and offset times of 53 out of 54 data sets from elderly participants. Cluster analysis separated the data into two groups. For both groups, the mean absolute error of the interval time was within 1 s when compared with the time recorded by a speech-language-hearing therapist. We believe that this biofeedback system for the Mendelsohn maneuver tolerates the 1 s delay. The wearable device is soft, lightweight, and easy for a patient to use alone. The efficacy of the device for the strengthening of muscles must be verified in a clinical study.**



***Index Terms*—** **Wearable sensors, Biomedical measurement, Stretchable strain sensors, Laryngeal elevation, Mendelsohn maneuver.**

I. Introduction

ASPIRATION pneumonia has been the seventh main cause of death in Japan for the past two years. 99% of the deaths from aspiration pneumonia occur in elderly individuals over 65 years of age [1], [2]. This condition is caused by pulmonary aspiration resulting from poor swallowing function [3], [4]. As society ages in Japan, the number of patients with aspiration pneumonia is increasing, presenting a serious problem for the medical community.

Training the muscles used for swallowing is an effective way for the elderly to reduce their risk of aspiration. One such swallowing rehabilitation technique is the Mendelsohn maneuver, in which the trainee voluntarily prolongs laryngeal elevation [5]. This method enhances the hyoid bone and the larynx, and strengthens the musculus constrictor pharyngis. Surveys in United States and Australia reported that the Mendelsohn maneuver was successfully implemented in the rehabilitation of dysphagia [6], [7]. Further, several studies have shown that this technique improves swallowing function and is effective for swallowing rehabilitation [8]-[12].

Recently, the use of biofeedback devices, utilizing surface electromyogram (sEMG), reflective photosensors, or accelerometers, has been proposed as a means of increasing the efficacy of the Mendelsohn maneuver. sEMG was found to be effective for training individuals in the maneuver by detecting the group of suprahyoid muscles involved in swallowing motions [13]. Ding *et al.* reported that sEMG data could be used to show the initiation and termination of muscle activity during both normal swallowing and the Mendelsohn maneuver [14]. However, sEMG requires treatment of the skin in advance, and it can be difficult for trainees to attach the sEMG electrodes

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themselves. Hayashi *et al.* proposed a wearable device with a photo-reflective sensor array [15], [16]. The sensor array was mounted on the anterior region of the neck using a flexion belt and measured the distance between the sensor array and the neck skin surface. The device could pinpoint the laryngeal position from the measured data, and trainees could observe the measurements using a visual feedback system with the wearable device. However, the photo-reflective sensor requires an air gap between the sensor and the neck skin, resulting in a thicker device that might inhibit voluntary neck motion in trainees. Accelerometer-based feedback systems have been used to measure the acceleration of the neck motion during the laryngeal elevation. Using this technique, the relationship between the accelerometry signals and a video feed from videofluoroscopy could be determined [17]. Indeed, a biofeedback system was used to show the acceleration signals to a patient on a computer screen [18], [19]. However, because the accelerometer chip was soldered to a solid substrate, the device would require custom fitting to individuals' neck size. Therefore, patients being trained in the Mendelsohn maneuver have not yet used these devices. Instead, these patients require a biofeedback device that is thin, lightweight, and easy to wear and use.

In this study, we report a wearable device with stretchable strain sensors for use in the Mendelsohn maneuver. The strain sensor is thin, stretchable, lightweight, and fits a curved surface, such as the neck. We embedded the strain sensor into a band-shaped device that can be worn around the neck. The device measures the change in the circumferential length of the neck. In addition, we developed an algorithm that can detect a laryngeal elevation based on these measurements. The algorithm uses dynamic time warping, and detects the onset and offset timings of the elevation in real-time. An experiment with elderly subjects revealed the effectiveness of the band-shaped device and algorithm.

II. Methods

A. Device

The sequential motions that occur during swallowing are shown in Fig. 1. The larynx begins moving upward at the onset time of the swallow and returns to its original position at the offset time, after the laryngeal elevation. The swallowing motion shortens the circumferential length of the neck during the laryngeal elevation. Speech-language-hearing therapists (STs) identify these changes in laryngeal elevation using visual inspection and palpation as evidence for the Mendelsohn maneuver. Hence, we focused on the measurement of the circumference-length change of the neck.

To measure the circumference-length change of the neck, we used a stretchable strain sensor [20]. The strain sensor was composed of three elastomer sheets and two electrodes, which were alternately layered. The electrodes were made of conductive particles. The elastomer sheets were highly flexible, stretchable, and exhibited a low stress of 0.83 MPa at 100% strain. Hence, the strain sensor could be easily stretched by hand. The thickness and density of the strain sensor were approximately 150 μm and 1.1 g/cm^3, respectively. These characteristics of the strain sensor made the sensor suitable as a wearable device. The capacitance of the strain sensor changed in concert with its change in length.

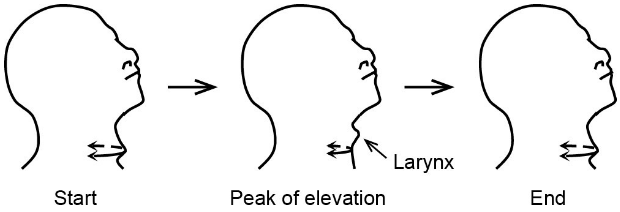


Fig. 1. The sequential motions of the neck and throat during swallowing.

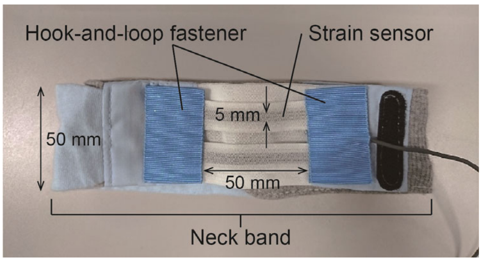


Fig. 2. Main components and sizes of the band-shaped device.

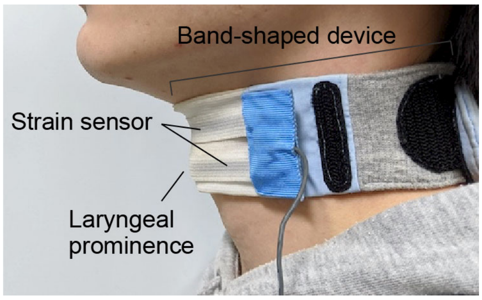


Fig. 3. Band-shaped device worn around the neck.

We incorporated the stretchable strain sensor into a band-shaped wearable device as shown in Fig. 2. The device was composed of a neckband and two strain sensors. The neckband was made of a stretchable fabric with hook-and-loop fasteners. The width and length of the neckband were 50 mm and 410 mm, respectively. Trainees could adjust the length of the neckband by tightening the band with the hook-and-loop fasteners. The length and width of the strain sensors were 50 mm and 5 mm, respectively, and the gap between the sensors was 5 mm. The strain sensors were covered with a white stretchable fabric. Both ends of the strain sensors were attached to the neckband using the hook-and-loop fasteners. The weight of the wearable device with the strain sensors was 35 g. To measure the length of the strain sensor, we developed a wireless communication unit. The strain sensors attached to the neckband were connected to the wireless communication unit, which included a capacitance-to-voltage converter, an analog-to-digital converter, and a wireless circuit. The wireless communication unit converted the capacitance of the strain sensors to voltage and sent the voltage data to a commercially available tablet computer by wireless. The size of the wireless communication unit was 80×65 and 15 mm in area and thickness. Its weight was 41 g. The sampling frequency was 10

Hz. Fig. 3 shows a trainee wearing the band-shaped device. The lower strain sensor was positioned over the larynx. In this case, the voltage in the lower sensor decreases during the laryngeal elevation. Then, the voltage returns to the initial level after the laryngeal elevation, as shown in Fig. 1.

B. Algorithm

We developed an algorithm that would allow users wearing the band-shaped device to observe the onset and offset times of the laryngeal elevation for the Mendelsohn maneuver in real-time. Before developing the algorithm, we obtained sample data in a preliminary experiment. The two typical time-series wave shapes are shown in Fig. 4(a) and (b). One is a bathtub shape, which resulted from trainees keeping their larynx at the highest position during the Mendelsohn maneuver. The other is a long-V shape. Although trainees tried to maintain the heightened position of their larynx, the larynx gradually lowered. In this case, the voltage of the strain sensor gradually increased, as in Fig. 4(b). A point in common between the bathtub and long-V shapes is a sharp drop of the voltage at the onset time. However, the changes in the data at the offset time exhibit distinct differences. Hence, we designed an algorithm that detects the onset and offset times using a common method and different methods for the two typical data types.

1) Detection of onset time

To detect the onset time, we developed a common algorithm for the bathtub and long-V shaped data. The algorithm calculates the absolute first-order difference of the measurements by:

$$dv[t] = |v[t] - v[t - 1]| \quad (1)$$

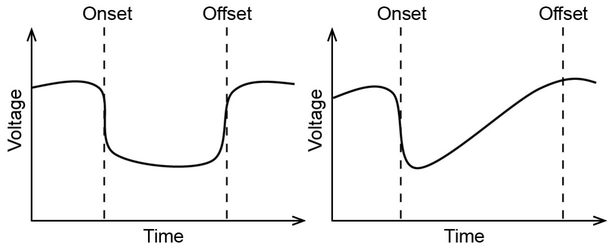
where $dv[t]$ and $v[t]$ are the absolute first-order difference and the voltage at time t, respectively. Fig. 5 illustrates the time-series difference calculated from the measurement data. The time-series difference shows a sharp change at the onset time. The algorithm detects this change using a threshold of $\mu + 1.2\sigma$, where μ is the average value of the time-series difference at rest and σ is the difference between the maximum and minimum differences at rest. The coefficient 1.2 of σ is determined by trial and error. If $dv[t]$ is higher than the threshold, the algorithm determines its time as the onset time.

2) Detection of offset time

After the detection of the onset time, the algorithm detects the offset time by dynamic time warping (DTW), which is one of the algorithms used for quantifying similarity between two sequential data sets [21], [22]. DTW allows partial expansion and contraction of sequential data and determines an optimal match and a DTW distance. In addition, DTW can add a constraint to the expansion and contraction in matching. The smaller DTW distance means a more similar relationship between two sequential data points. In this study, we created template data for the bathtub and long-V shapes to calculate similarities with the data measured using the strain sensor. The algorithm has different conditions for the offset time detection for the bathtub and long-V shapes as follows.

・ For the bathtub shape:

If the following conditions hold simultaneously, the algorithm detects the time as the offset time.



(a) Bathtub shape. (b) Long-V shape.

Fig. 4. Typical waveform of measured data during the Mendelsohn maneuver.

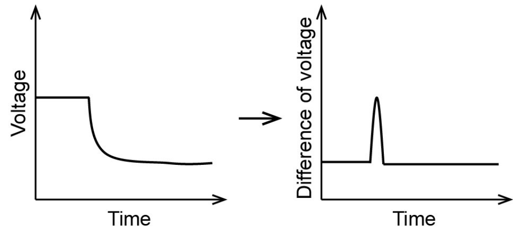


Fig. 5. Absolute first-order difference calculated from measured data.

(a1) The DTW distance is small:

$D(X[t_{on} : t], Y) \leqq \varepsilon_1$.

(a2) The DTW distance decreases rapidly:

$D(X[t_{on} : t - t_{int}], Y) - D(X[t_{on} : t], Y) > \varepsilon_2$.

$X[t_{on} : t]$ and Y are the measurement data from the onset time t_{on} to the current time t and the template data, respectively. $D(X[t_{on} : t], Y)$ is the DTW distance between $X[t_{on} : t]$ and Y. ε_1 and ε_2 are the thresholds of the two conditions. t_{int} is an interval time. The condition (a1) evaluates the similarity between the measurement data and the template data. In the case of the bathtub shape, the DTW distance decreases rapidly after the right slope of the bathtub. The condition (a2) evaluates the rapid decrease in the DTW distance.

・ For the long-V shape:

If the following conditions hold simultaneously, the algorithm detects the time as the offset time.

(b1) The DTW distance is small:

$D(X[t_{on} : t], Y) \leqq \varepsilon_1$.

(b2) SPRING finds the optimal subsequence.

The condition (b1) is the same as (a1). The algorithm uses SPRING [23], [24], which detects the optimal subsequence in data streams based on the minimum DTW distance matrix. The DTW distance decreases gradually in the right slope of the long-V shape. In this case, even if the DTW distance at time t is smaller than the threshold, the DTW distance at time t+1 may be smaller than the DTW distance at time t. Hence, the algorithm has to find the terminal of the right slope of the long-V shape. SPRING finds the optimal subsequence from the measurement data and the algorithm detects the terminal time as the offset time.

At the time when the onset time is detected, the algorithm is not able to discriminate whether the measurement data is the bathtub shape or the long-V shape. The algorithm calculates the DTW distances, along with the conditions for both the bathtub and long-V shapes, for every new measured data point, with multiple template data for the shapes. Hence, when the offset time is detected, the shape of the measurement data is also determined.

III. Experiment

All procedures were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments. This study was approved by the Ethical Committee of Graduate School of System Informatics, Kobe University (Permission number: 30-02), the ethical standards of the Committee on Human Experimentation at the Graduate School of Health Sciences, Kobe University (Permission number: 805) and the Ethical Committee of Mie Central Medical Center (Permission number: MCERB-201832).

The main target of the wearable device is the elderly. Hence, we obtained measurement data from subjects 60 years or older. The subjects did not have a respiratory disease or heart failure, which is a contraindication for the Mendelsohn maneuver. In the experiment, subjects wore the band-shaped device with one of the strain sensors on the laryngeal prominence as shown in Fig. 3. The subjects sat and rested for 3 s before the laryngeal elevation. Then, they started swallowing with 3 ml of water and kept their larynx at the highest position as long as possible. The wearable device measured the circumference-length change of the neck during the experiment. Simultaneously, an ST detected the onset and offset of the laryngeal elevation by palpation and sent their times to the tablet PC using a wireless push button. The tablet PC connected to the band-shaped device and the push button recorded the data from them. We checked that the human subjects were able to perform the Mendelsohn maneuver in advance. The human subjects were 28 healthy volunteers of average characteristics: female:male = 10:18 and mean age: 70.9 ± 6.2 years. The subjects comfortably wore the neckband without the feeling of suffocation during the experiment. We obtained 54 data sets from the subjects. Hereafter, we use only the data measured from the strain sensor on the laryngeal prominence. The measurement data were normalized to fall within a range between 0 and 1.

A. Cluster analysis

To check the tendency of the measured data, Ward's method in hierarchical cluster analysis was used to separate the data [25]. In the analysis, the data were cut between the onset and offset times detected by the ST and were expanded or contracted to the time interval of 4.5 s. Fig. 6 shows a cluster dendrogram of the measured data, where the horizontal axis shows the index numbers of the data. The measured data were mainly separated into two groups. The left and right groups in Fig. 6 are shown in Fig. 7(a) and 7(b), respectively. Fig. 7(a) shows the larynx kept at the highest position before falling. On the other hand, Fig. 7(b) shows that the larynx fell gradually to the original position. We verified that the measured data from the elderly subjects exhibit both the bathtub and long-V shapes.

B. Template data

The algorithm in section B requires template data to detect the onset and offset times. Next, we created the template data. To avoid the template data depending on a particular set of measured data, the template data were randomly determined based on the waveforms of the measured data.

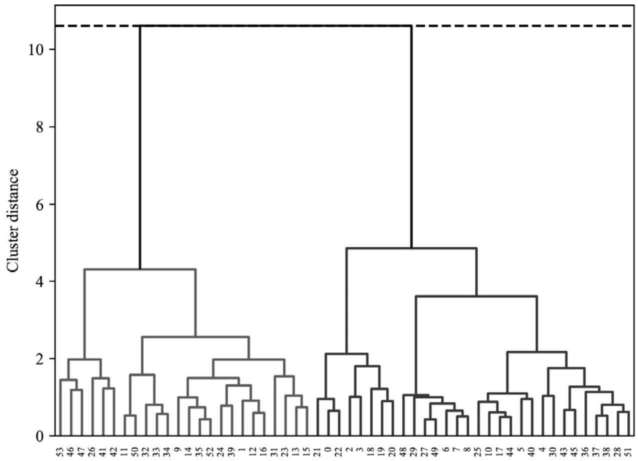
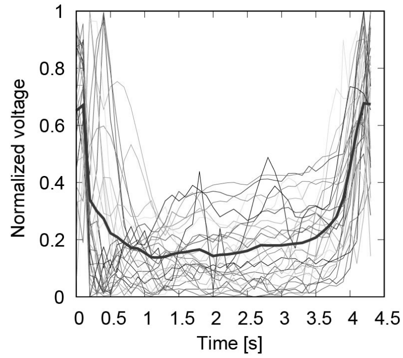
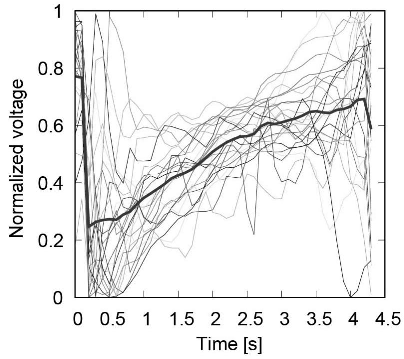


Fig. 6. Cluster dendrogram of measurement data in the Mendelsohn maneuver. The horizontal axis shows the index number from 0 to 53 of measurement data.

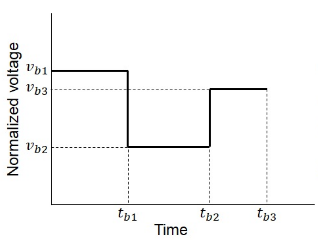


(a) Bathtub shape.

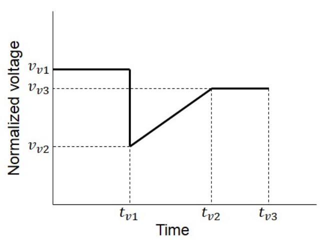


(b) Long-V shape.

Fig. 7. Two groups of measured data separated by cluster analysis. The bold line shows the averaged data.



(a) Bathtub shape.

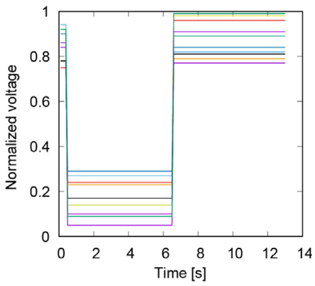


(b) Long-V shape.

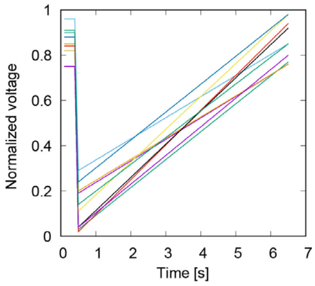
Fig. 8. Schemas of template data.

TABLE I
RANGE OF PARAMETERS IN NORMALIZED VOLTAGE FOR DETERMINATION OF TEMPLATE DATA

v_{b1}	v_{b2}	v_{b3}	v_{v1}	v_{v2}	v_{v3}
0.75–1.0	0.0–0.3	0.5–1.0	0.75–1.0	0.0–0.2	0.75–1.0



(a) Bathtub shape.



(b) Long-V shape.

Fig. 9. Template data for the bathtub and long-V shapes.

The analysis showed that the measured data were separated into bathtub or long-V shapes. Hence, the schemas are shown in Fig. 8(a) and 8(b). Because DTW in the algorithm determines the DTW distance between the measurement data and the template data by expansion and contraction, the parameters of the time were constant as follows: t_{b1}=0.5, t_{b2}=6.5, t_{b3}=13, t_{v1}=0.5 and t_{v2}= t_{v3}=6.5 s. In this case, t_{b1} and t_{v1} are the onset timings, and t_{b2} and t_{v2} are the offset timings. The time interval between the onset and offset times is 6 s. DTW in the algorithm uses a slope constraint [21], which limits the expansion and contraction of the data from 1/3 to 3 times. Thus, the template data can be used with the measured data in the time interval from 2 to 18 s. The six normalized voltages from v_{b1} to v_{v3} were randomly determined. The ranges of the random values are shown in Table I. Fig. 9(a) and Fig. 9(b) show the template data for the bathtub and long-V shapes, respectively. Each shape has ten templates. In the following experiment, if 3 of 10 templates met the condition described in section II-B, the algorithm determined the offset time by averaging the offset times.

C. Detection of onset and offset times

The algorithm determined the onset and offset times of the laryngeal elevation based on 54 measured data sets. The onset times were detected in all 54 data sets. The offset times were detected in 27 data sets with the bathtub shape and 26 data sets with the long-V shape. The algorithm could not detect only one offset time. Typical examples of bathtub and long-V shapes are shown in Fig. 10(a) and Fig. 10(b). The upper plots show the measured data detection times. The lower plots show the DTW distances between the measured data and the template data. The algorithm determined the DTW distance after 2 s from the onset time due to the slope constraint. When the DTW distances decreased, the algorithm detected the offset times. Fig. 10(c) shows an example of a detection failure of the offset time. In this figure, the measured data had a high peak after the detection of the onset time. Because the measured data was not similar to the template data, the DTW distances did not decrease in comparison with Fig. 10(a) and Fig. 10(b).

TABLE II
MEAN ABSOLUTE ERROR OF DETECTED ONSET, OFFSET AND INTERVAL TIMES OF LARYNGEAL ELEVATION AND THEIR STANDARD DEVIATION

	Bathtub shape			Long-V shape		
	Onset	Offset	Interval	Onset	Offset	Interval
MAE [s]	0.37	0.29	0.41	0.54	0.70	0.77
SD [s]	0.30	0.63	0.59	0.41	0.60	0.49

Table II shows mean absolute errors (MAEs) and standard deviations of the onset and offset times and their interval times detected using the algorithm and the ST, with the exception of the failed offset detection. The MAEs of the interval times were within 1 s.

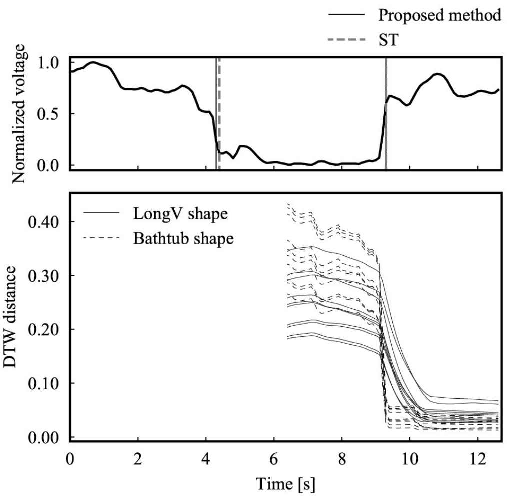
IV. Discussion

The hierarchical cluster analysis determined the distances between the measured data. The dendrogram in Fig. 6 visualizes their relationship. The measured data were mainly separated into two groups. The group with the bathtub shape corresponded to subjects who kept their larynx at the highest position during the Mendelsohn maneuver. The group with the long-V shape corresponded to subjects whose larynx fell gradually during the Mendelsohn maneuver. The difference between the groups might distinguish the quality of the Mendelsohn maneuver.

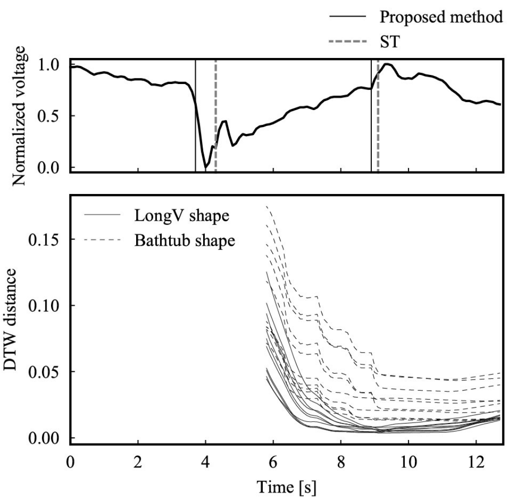
A failed case of offset time detection using the algorithm is shown in Fig. 10(c). The voltage rose after the onset time and changed in a manner mimicking the bathtub shape. Because the subject had a muscle disease, the circumferential length of the subject's neck may have changed before and after the maneuver. When we normalized the data, the normalized data had low values at rest before and after the Mendelsohn maneuver, which resulted in differences from the bathtub shape template data. Hence, the algorithm missed the detection of the offset time. The normalization process is necessary to reduce the difference between the maximum and minimum in the measured data. However, additional processes are required in some cases, such as Fig. 10(c), to detect the offset time.

The algorithm detected the onset and offset times from 53 data sets out of 54 in 28 elderly subjects. The onset times were detected using the threshold for the first-order difference. The MAEs between them and the times detected by the ST were within 1 s. Regarding the offset times in Fig. 10(a), the algorithm detected the offset times for the bathtub shape without a large error because the DTW distances rapidly fell near the offset time determined by the ST. In the case of the long-V shape, the algorithm detected the offset times based on the optimal match determined using SPRING. The algorithm using multiple conditions for detection worked effectively. Hence, the MAEs between the interval times for the algorithm and the ST were within 1 s. This result means that a biofeedback system using this algorithm has a 1-s delay at most. Although the other devices mentioned in section I were successful in some ways, their accuracy was not validated using a method like MAE, determined by combining the device and an algorithm. In contrast, we validated the accuracy of onset and offset times using the wearable device and the algorithm described in this paper. We do not consider the 1-s delay to be a serious problem for assessing the Mendelsohn maneuver with a biofeedback system.

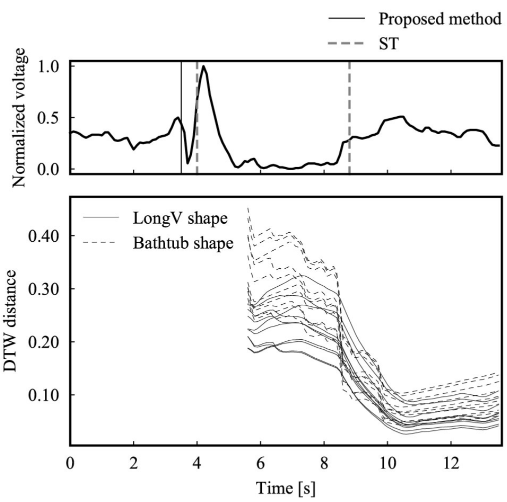
The wearable device and the algorithm in this study have some limitations. A trainee is required to sit without moving the head and body during the Mendelsohn maneuver. Although the



(a) Bathtub shape. The offset time detected by the algorithm was almost coincident with that of the ST.



(b) Long-V shape.



(c) A case of failed offset time detection.

Fig. 10. Typical examples of the detection of the onset and offset times. The upper plots show the measurement data and the detection times by the proposed method and ST. The lower plots show the DTW distances calculated with all bathtub and long-V template data.

algorithm detected the onset and offset times of the laryngeal elevation without a large error in the experiment, this method may prove difficult for subjects who exhibit frequent motion of the head or body. The DTW uses the slope constraint and can detect the interval time from within 2 to 18 s of the laryngeal elevation; thus, the interval time is a limitation of the algorithm. However, in medical sites, the ST does not recommend that the trainee stop his breathing for more than 18 s during the maneuver. Hence, this limitation is not important in practical use. The measured data in Fig. 10(c) was designated as having the bathtub shape. However, if additional data is collected from more subjects, a third group may emerge. Thus, more experimental data must be obtained to reduce errors.

V. Conclusion

This study describes a wearable device for training in the Mendelsohn maneuver. The wearable device was designed to be comfortable for the wearer, as it contained thin, stretchable, and lightweight strain sensors. We also developed an algorithm to detect the onset and offset times of the laryngeal elevation. The algorithm detected the onset time based on the first-order difference and the offset time based on the DTW distance. From 54 measured data sets from 28 elderly subjects, the algorithm was able to detect the onset and offset times for 53 out of 54 data sets. The MAE of the interval time of the laryngeal elevation between the algorithm and the ST was within 1 s. We believe that the biofeedback system for the Mendelsohn maneuver tolerates the 1-s delay present in this system.

Future work will focus on performing additional experimental trials with elderly subjects and verifying the data shape clusters to heighten the accuracy of the detection of the onset and offset times. The efficacy of the biofeedback system will then be confirmed in a clinical study of dysphagia patients.

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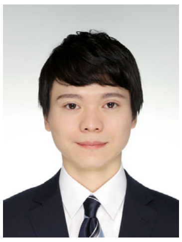

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