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Wearable tactile sensor system for reading braille

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Abstract. This paper is a study on the development of a wearable sensor system for reading Braille. The study is intended to develop a compact tactile sensor system which uses a PVDF (Polyvinylidene Fluoride) film as the sensory receptor. The sensor is mounted onto a fingertip and moved over Braille manually to obtain the sensor output. Since the unsteady movements yield variations in the waveforms, a robust recognition system is required. The recognition system consists of three components as follows. First, the signal inputted to the system is divided into individual signals regardless of the variations in the waveforms. Next, those signals are transformed into effective feature vectors in order to suppress the variations. Finally, those vectors are classified and the results are obtained. In the process, minimum-distance classifiers and neural classifiers are used. For the investigation of experimental verification, test signals are inputted to the recognition system and the performance of the system is evaluated. The obtained results show that the wearable sensor with the recognition system is effective to recognize Braille.

Keywords: Braille, recognition system, tactile sensor, PVDF film, measurement, signal processing

1. Introduction

Braille is a language for visually disabled persons and it is regarded as an important communication means for them. However, the learning of Braille requires great efforts, especially for those who acquired their disability during the course of their life. Reportedly, some people are depressed by the difficulty of learning it. In addition, support instruments for this learning have not been developed sufficiently, and Braille has not been utilized effectively. For this reason, we have studied a wearable sensor system for reading Braille as the convenient tool to support the learning and as the portable device which is available anywhere. The sensor is attached to a fingertip and the sensor system recognizes Braille by just scanning it manually.

Although many studies have been already made on Braille reading machines [1–4], most studies are focused on optical recognition using CCD cameras or other optical devices. They are complicated and precise structures including many circuits and cables. The additional issues associated with those approaches are the manufacturing cost, size and durability. Thus, a wearable sensor system for reading Braille has not been developed yet.

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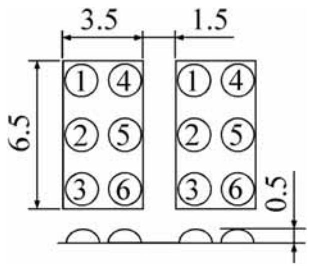

Units: mm

Fig. 1. Braille format.

This paper is concerned with the development of a wearable sensor system for reading Braille. The sensor uses a PVDF (Polyvinylidene Fluoride) [5–7] film as the sensory material and generates characteristic signals for each letter. The PVDF film is a piezoelectric polymer film. It has high sensitivity and is thin, lightweight, flexible and low cost. The wearable sensor can be compact and low cost by using the PVDF film. We have designed the fundamental structure of the sensor and investigated the effect of the sensor's traveling speed using a mechanical slider [8,9]. Subsequently, the fundamental recognition method that can recognize Braille regardless of the speed has been developed, and the experimental verification has confirmed that the proposed sensor system is effective to recognize Braille. However, a sensor system used as the wearable system has never been examined.

In this study, the structure of the wearable sensor is designed, and the sensor is mounted onto a fingertip to move over Braille manually as the wearable system. The unsteady movements yield variations in the waveforms. Thus, a robust recognition system is required. The proposed recognition system consists of three components as follows. First, an input signal is divided into individual signals regardless of the variations in the waveforms. Next, those signals are transformed into effective feature vectors in order to suppress the variations. Finally, those input vectors are classified and the results are obtained. Multi-layer perceptrons [10–12] are used to classify the input vectors. For comparison, minimum-distance classifiers [13] are also used. For the investigation of experimental verification, test signals are inputted to the recognition system and the performance of the system is evaluated. The wearable sensor system is verified as to whether it is effective to recognize Braille.

2. Braille

Braille is represented by patterns of raised dots so that persons can read it by the touch sensation of their fingertip. The configuration of Braille is shown in Fig. 1. The size of a single letter is 6.5 mm by 3.5 mm, with the dots 0.5 mm in height. A string of letters is arranged in a row at intervals of 1.5 mm and read from left to right. The objects recognized with the system consist of 46 letters which are the Japanese kana alphabet from "a" to "n". Therefore, there are 46 classes as the classification problem.

3. PVDF sensor

The detailed structure of the wearable sensor is shown in Fig. 2. The wearable sensor uses a PVDF film as the sensory material. Braille is small and the size varies depending on printing methods. The use of multiple PVDF films as the sensing elements may cause the complex and fragile structure of the sensor and produce the undesirable output by pressure distribution over adjacent films. The sensor

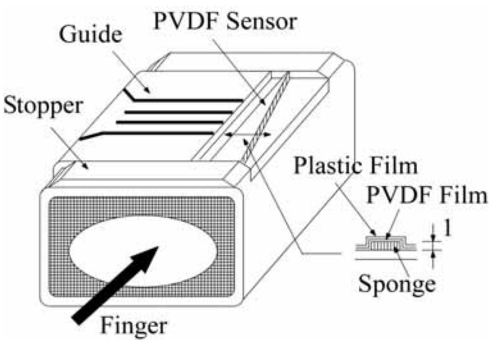

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Fig. 2. Geometry of sensor.

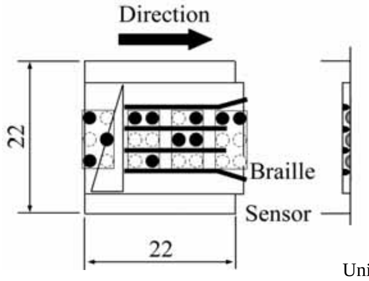

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Fig. 3. Position between sensor and Braille.

developed has one sheet of PVDF film and it leads to the simple structure. A fingertip is inserted into the sensor applying the sensing area to Braille. The sensor is moved over Braille manually from left to right to obtain the output. The position between the sensor and Braille during the movement is shown in Fig. 3. Since the sensor is a tactile sensor, the dynamic contact between the sensory receptor and Braille provides the output.

The base of the sensor is a stainless shell, on which a sponge rubber, a sheet of PVDF film with an electrode patch and a protective plastic film are stacked in sequence. The shape of the sponge rubber is a right-angled triangle whose two sides forming the right angle are 12.5 mm and 3 mm. The long side of the right-angled triangle other than the hypotenuse is arranged perpendicular to the moving direction of the sensor. The time length of contact with each dot in a vertical row of Braille varies according to the dot's position, which makes waveforms from each Braille differential shape.

Stoppers are fixed on both upper and lower sides of the sensor surface in order to suppress the variation of the contact depth. Additionally, guides are mounted at the side of the sensory receptor, which allows the sensor to move straight along Braille.

4. Measurement system

The experimental setup is shown schematically in Fig. 4. The sensor was moved over strings of letters manually to obtain the output for speed of about 50 mm $s^{-1} \sim 200$ mm s^{-1}. The strings were composed of 3 or 5 letters, and 1200 string's waveforms (total number of waveforms from single letters is 5520)

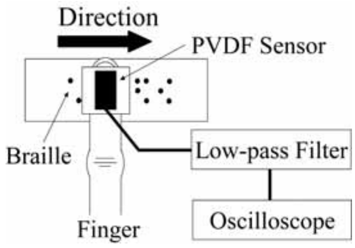
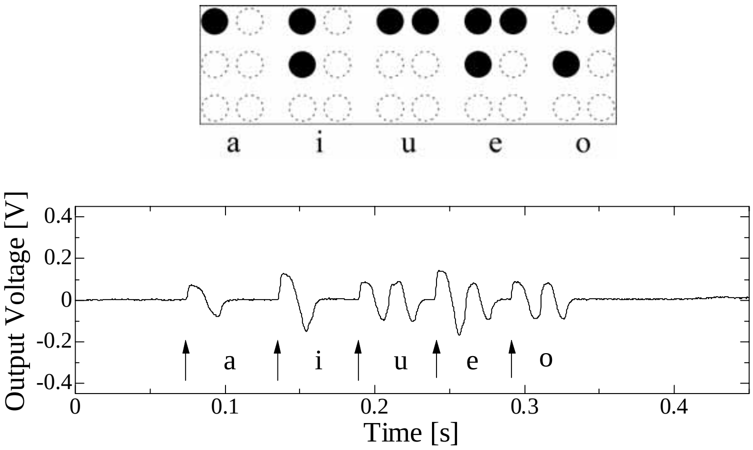
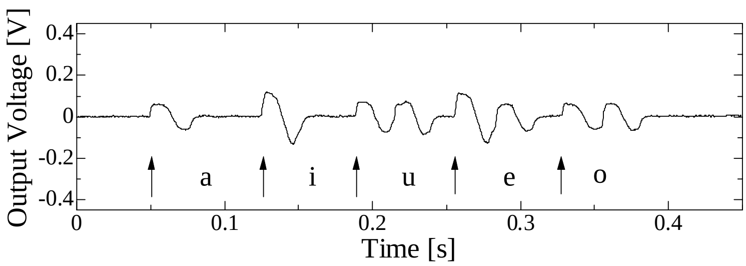


Fig. 4. Experimental setup.



(a) Output 1

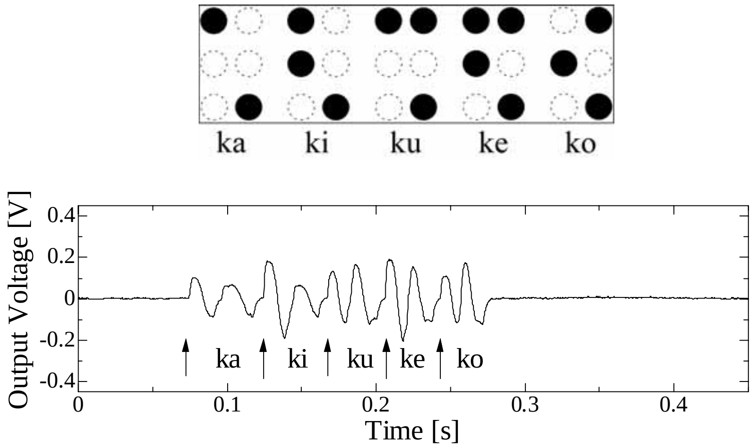


(b) Output 2

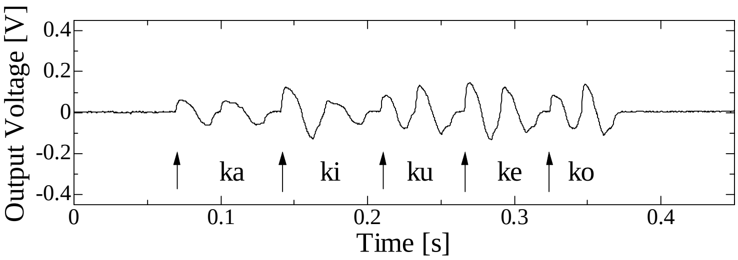
Fig. 5. Sensor output of "a-i-u-e-o". (a) Output 1; (b) Output 2.

were measured by 6 healthy subjects who were initially trained in how the sensor used. The start position of the sensor was by the left side of the strings, and the sensor was moved over Braille toward the end. The sensor can follow free fingers tracking Braille for the perception of position and direction of Braille if necessary.

A low-pass filter of cutoff frequency 1 kHz was inserted after the sensor to remove the overlap of noises to the sensor signal. The signals were observed with a digital storage oscilloscope of sampling frequency 5 kHz. The data were sent to a personal computer and memorized to study the recognition system.



(a) Output 1



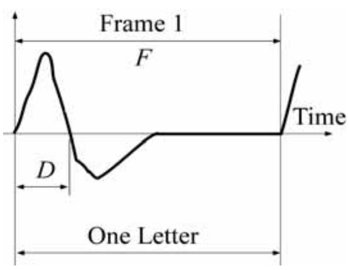
(b) Output 2

Fig. 6. Sensor output of "ka-ki-ku-ke-ko". (a) Output 1; (b) Output 2.

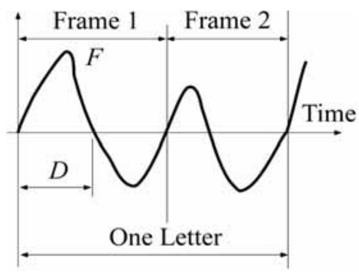
5. Sensor output

Some examples of the sensor output of one subject are shown in Figs 5 and 6. Since the sensor is slid over strings of letters manually, the movement is more unsteady than the movement by the mechanical slider used in the previous studies [8,9]. The effects include the variation of the speed, contact depth, angle of the sensor to the moving direction and so forth. Although the amplitude and the time length of individual waveforms are changed, the shape of the waveforms is not affected. This reveals that a single letter is short enough and the movement over it is almost steady. For this reason, we have attempted to recognize Braille from the output of the PVDF sensor without additional sensors for the correction of the movement.

Some definitions of waveforms are given as follows. A waveform is a sequence of a peak and a valley. Therefore, rising edges are detected using a voltage threshold of 0.02 V as the process of the recognition system to handle the waveforms easily. The section between adjacent rising edges is designated as a single frame. The individual waveforms are classified into two patterns, designating those waveforms composed of only single frame as Pattern 1, and those composed of two frames as Pattern 2. The number of classes in Pattern 1 is 5 ($= c_1$) and Pattern 2 is 41 ($= c_2$). Figure 7 illustrates these two patterns. In the figure, F is the time length of the first frame, D is the time length of the first region enclosed by the waveform and the time axis.



(a) Pattern 1



(b) Pattern 2

Fig. 7. Pattern of waveform. (a) Pattern 1; (b) Pattern 2.

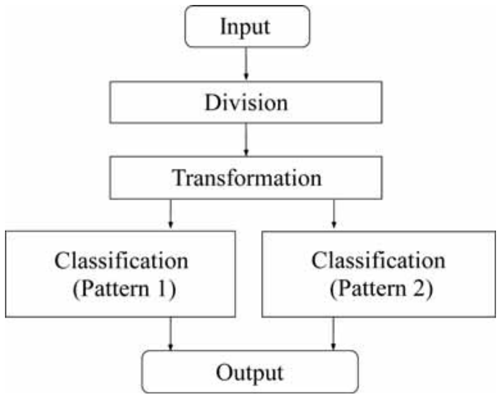


Fig. 8. Processes of recognition system.

6. Recognition system

In this section, we describe the recognition system which recognizes a string of letters. The recognition system is shown in Fig. 8. It was built on a personal computer, and all the processing was performed with the computer. The aim is to recognize Braille from the sensor output containing unknown variations. The recognition system is consists of three components as the different operation. First, an input signal is divided into individual signals regardless of the variation in the waveforms and the pattern of each waveform is decided concurrently. Next, those signals are transformed into effective feature vectors. Finally, to classify the vectors, the classifiers of corresponding patterns are selected and the classification results are obtained.

To study the recognition system, the obtained 1200 original waveforms were separated into a training set and a test set half-and-half. The training set was used to design the recognition system. The test set was used to evaluate the performance of the system. Both of the sets have 600 waveforms and the total number of single letter's waveforms in each set is 2760, which corresponds to 60 single letter's waveforms per class. The number of waveforms of Pattern 1 is 300, and Pattern 2 is 2460.

7. Division process

Sensor signals are obtained in the form of the continuous waveform of single letters as shown in Figs 5 and 6. Therefore, the first process of the recognition system is the automatic division of an input signal

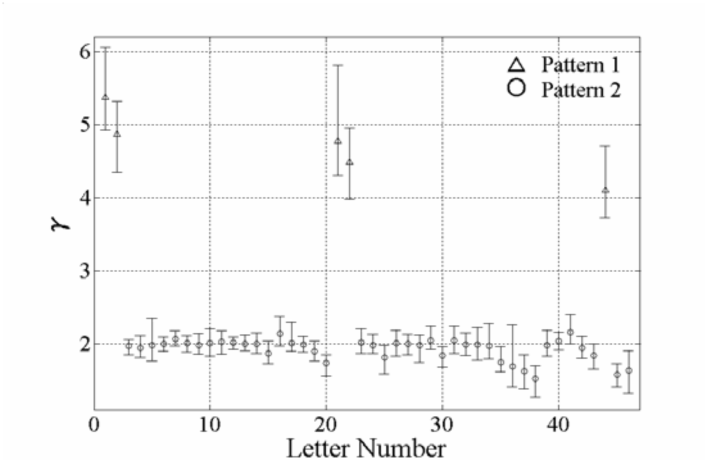


Fig. 9. Distribution of γ.

into individual signals.

All single letter's waveforms in the training set were divided manually. The division process was developed through an analysis to the divided waveforms. The developed process is conducted as the following steps.

[Step 1] Detection of frames

Detect frames from an input signal, and assign the number i (= 1, 2, $\ldots$, n) to each frame in order. The n indicates the final frame in the input signal. Subsequently, initialize i to 1 and go to the next step.

[Step 2] Detection of single letter's waveforms

Analyze the frame i to check whether it is Pattern 1.

Case 1: If Pattern 1, divide the frame i as the single letter's waveform of Pattern 1. The present i is updated by adding 1 in the form $i \leftarrow i + 1$, and the process goes to the next step.

Case 2: If not, combine the frame i with the frame $i + 1$ and divide the combined frame as the single letter's waveform of Pattern 2. The present i is updated by adding 2 in the form $i \leftarrow i + 2$, and the process goes to the next step.

[Step 3] Finish criterion

Case 1: If $i < n$, return to the Step 2 and continue.

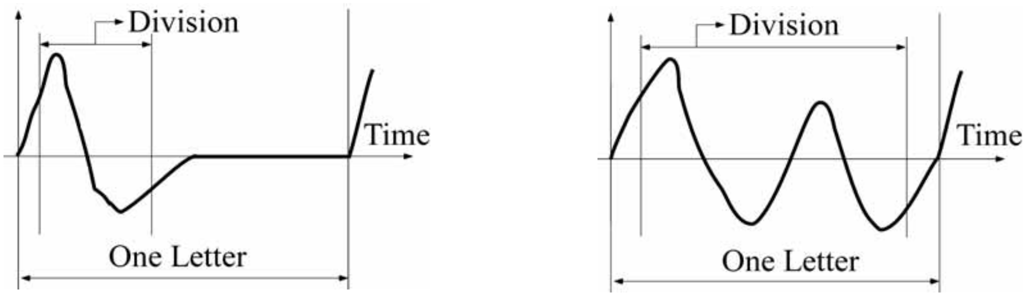
Case 2: If $i = n$, divide the frame i as the single letter's waveform of Pattern 1 and finish this process.

Case 3: If $i > n$, finish this process.

In the Step 2, a method to distinguish the two patterns is required. To fulfill the requirement, a simple feature

$$\gamma \equiv D_i^{-1} F_i \tag{1}$$

is used. We expect the feature to be invariant to the scale of waveforms. The values of γ for all single letter's waveforms in the training set were calculated, and the result is shown in Fig. 9. The horizontal



(a) Pattern 1 (b) Pattern 2

Fig. 10. Transformation process. (a) Pattern 1; (b) Pattern 2.

axis indicates the number of letters from "a" to "n", and the vertical axis indicates the values of γ. Since there is a clear boundary between the two patterns, the discriminant function

$$s(\gamma) = \gamma - 3 \tag{2}$$

is proposed. All single letter's waveforms in an input waveform are divided by applying the rule,

if sgn($s(\gamma)$) $= 1$ then Pattern 1 else Pattern 2,

to the frame i analyzed in the Step 2.

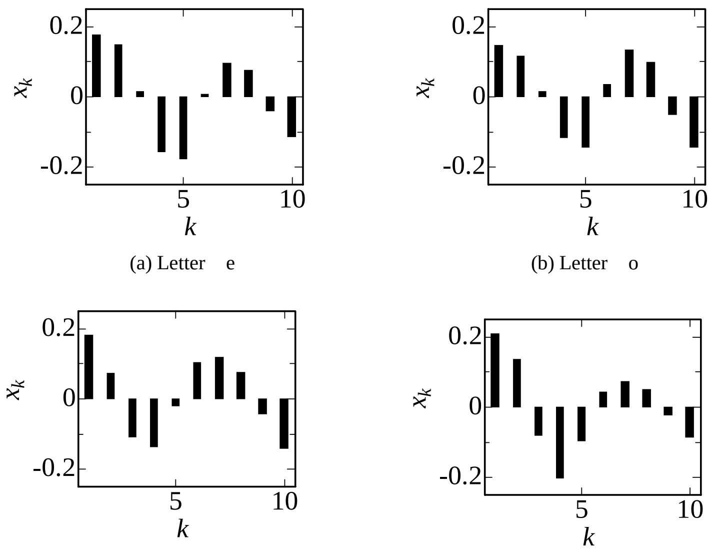
To examine the performance of the division process, we applied the process to all waveforms in the test set. The single letter's waveforms were divided automatically with the success rate of 99.89%, and we have confirmed that the division process can be implemented with accuracy. The error was due to the detection of rising edges at undesired points. The single letter's waveforms which could not be divided successfully were divided manually and also used to conduct the following experiments.

8. Transformation process

In the next process of the division process, each divided waveform is transformed into an appropriate vector form for the classification. We used the following transformation method to suppress mainly the elasticity of waveforms to the directions of the time axis and voltage axis. First, the sections of 20% area of the initial peak and 30% area of the final valley in each waveform are neglected from the section for the transformation as shown in Fig. 10. Next, each waveform is divided into m segments for the section, and the mean amplitude in each segment is calculated as the element of the vector. Moreover, each vector $\boldsymbol{e}$ are normalized by the sum of the absolute value of each element represented as

$$\boldsymbol{x} = \left(\sum_{i=1}^{m} |e_i|\right)^{-1} \boldsymbol{e}. \tag{3}$$

The single letter's waveforms in the training set and test set were transformed into the vector form using the above process to examine the classification process. Let $\boldsymbol{v}$ be a training vector, and let $\boldsymbol{x}$ be a test vector as an input vector. Some examples of normal vectors are represented in Fig. 11. Each vector has differential values in each element in dependence on each letter.



(a) Letter e
(b) Letter o
(c) Letter ka
(d) Letter ki

Fig. 11. Examples of vector ($m = 10$). (a) Letter "e"; (b) Letter "o"; (c) Letter "ka"; (d) Letter "ki".

9. Classification process

In the classification process, multi-layer perceptrons were used to classify the input vectors. Any continuous function from input to output can be implemented in a three-layer net, given sufficient number of hidden units, proper nonlinearities, and weights. The backpropagation is one of the simplest and most general methods for supervised training of multi-layer perceptrons [10].

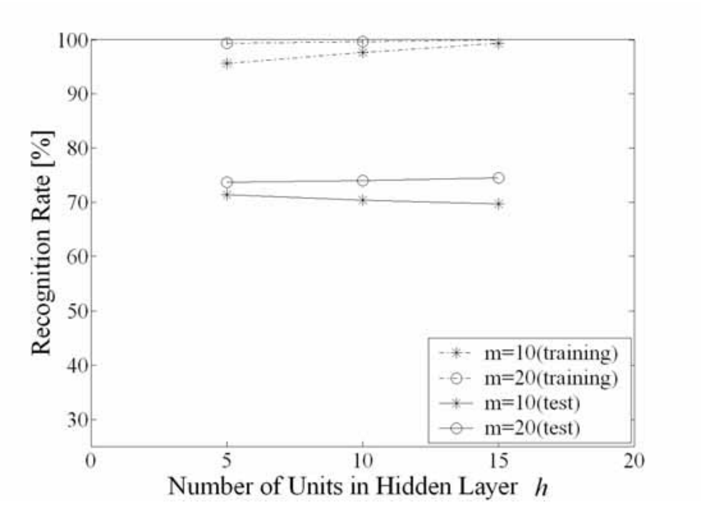
We used the neural classifiers with a three-layer net, and the weight change method used in training the network was modified backpropagation in the batch mode. Networks were trained independently for each pattern. Each network classifies the corresponding input vectors of length m into c classes. Here, $c = c_1$ and $c = c_2$ correspond to each network of Pattern 1 and Pattern 2. There are $m + 1$ units in the input layer, $h + 1$ units in the hidden layer, and c units in the output layer. The number of units in the hidden layer was adjusted experimentally. The discriminant functions are in the form

$$g_k(\tilde{\boldsymbol{x}}) \equiv f\left(\sum_{j=1}^{h} w_{kj} f\left(\sum_{i=1}^{m} w_{ji}\tilde{x}_i + w_{j0}\right) + w_{k0}\right), \qquad k = 1, 2, \ldots, c \tag{4}$$

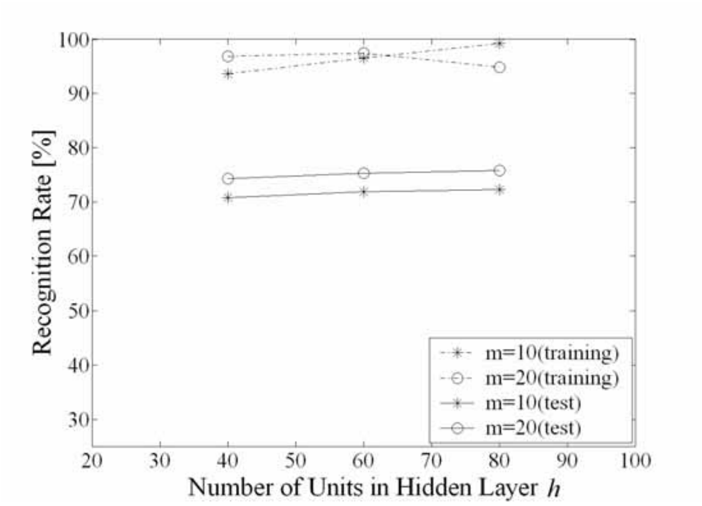
where

- w_{kj}: the weight assigned to the link from the jth ($j = 0, 1, \ldots, h$) unit of the hidden layer to the kth ($k = 1, 2, \ldots, c$) unit of the output layer, and $j = 0$ indicates the bias unit.
- w_{ji}: the weight assigned to the link from the ith ($i = 0, 1, \ldots, m$) unit of the input layer to the jth ($j = 1, 2, \ldots, h$) unit of the hidden layer, and $i = 0$ indicates the bias unit.
- f: the logistic sigmoid activation function
- $\tilde{\boldsymbol{x}}$: the input vector normalized in the form

$$\tilde{x}_i = \frac{x_i - v_{\min}}{v_{\max} - v_{\min}}, \; i = 1, 2, \ldots, m \tag{5}$$



(a) Pattern 1

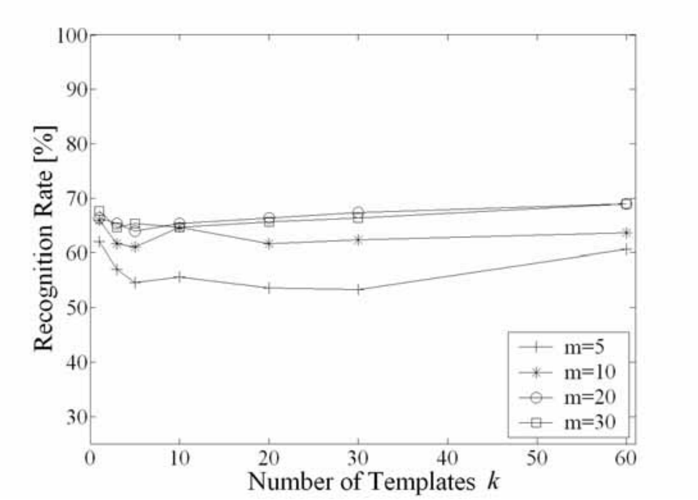


(b) Pattern 2

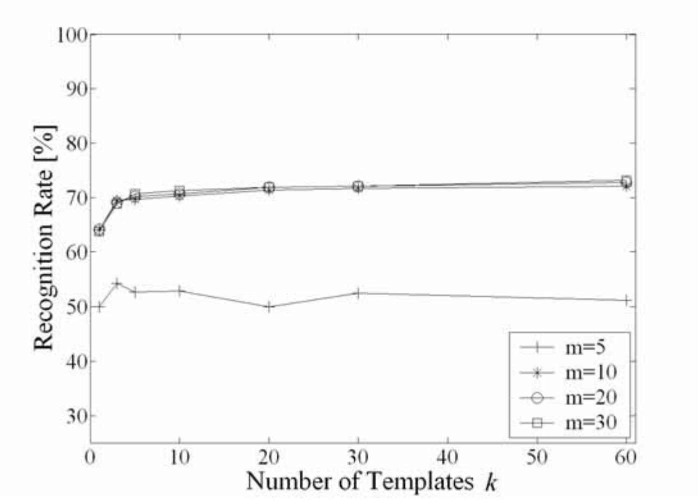
Fig. 12. Results of neural classifiers. (a) Pattern 1; (b) Pattern 2.

where $v_{\min}$ is the minimum value of the element in the training vectors, and $v_{\max}$ is the maximum value.

The values of the discriminant functions always lie between 0 and 1. In the training, the target vector for the training vector of a class c is set at 0.9 for the cth element, and 0.1 for the others considering some tolerance. Each network classifies the input vectors according to which discriminant function is largest. The training error on a training vector is the sum over the output units of the squared difference between the target output and the actual output. The total training error, the sum of the errors on all training vectors, was reduced enough using a conjugate gradient descent algorithm. The maximum number of epochs in the training was set at 10000.



(a) Pattern 1



(b) Pattern 2

Fig. 13. Results of minimum-distance classifiers. (a) Pattern 1; (b) Pattern 2.

10. Experimental verification

The performance of the classifiers are verified experimentally in this section. The test vectors were inputted to the classifier of corresponding patterns. There are 300 test vectors of Pattern 1, and 2460 test vectors of Pattern 2. Since the number of classes in each pattern is different (Pattern 1 is 5 ($= c_1$) and Pattern 2 is 41 ($= c_2$)), let the mean recognition rate for all classes be

$$Q = (c_1 + c_2)^{-1}(c_1Q_1 + c_2Q_2), \tag{6}$$

where Q_1 and Q_2 correspond to the maximum recognition rate of Pattern 1 and Pattern 2 for a classification method.

Figure 12 shows the recognition results for each pattern, plotted against the number of units in the hidden layer. The results for the training vectors and test vectors are described. The dimensions of the vectors m were 10 and 20. The number of units in the hidden layer examined was 5, 10 and 15 for Pattern 1, and 40, 60 and 80 for Pattern 2. The recognition rates for the training vectors are in excess of 90% at every condition. For the test vectors, the maximum recognition rate for Pattern 1 is 74.47% ($m = 20$, $h = 15$), and for Pattern 2 is 75.81% ($m = 20$, $h = 80$). In this case, the mean recognition rate for all classes is 75.66%. The results confirm that the sensor system has enough potential to recognize Braille. The recognition rate for the test vectors was lower than the one for the training vectors by 20% or more. The explanation is that there are numbers of target classes and it reduces the quality of training. Indeed, we confirmed that the recognition results were improved with reduced target classes.

For comparison, minimum-distance classifiers [13] were also used. The templates in each class were edited using k-means clustering for the multi-template method and registered in the computer beforehand. The metric used in the classification was the Euclidean formula in m dimensions. The rule for classifying an input vector was to assign it the label associated with the nearest template. The recognition results using the classifiers are shown in Fig. 13. The horizontal axis indicates the number of templates in each class, and the vertical axis indicates the recognition rate for the test vectors. The results for the training vectors are omitted in the figure. The dimensions of the vectors m were 5, 10, 20 and 30. The maximum recognition rate for Pattern 1 is 69.00 % (m =20, $k = 60$), and for Pattern 2 is 73.13% ($m = 30$, $k = 60$). In this case, the mean recognition rate for all classes is 72.68%. Although the classifiers require redundant storage capacity and computational complexity especially in the case of $k = 60$, the mean recognition rate is lower than the one of the neural classifiers by about 3%.

In addition to improving the recognition methods, the optimal design of the sensor structure will also improve the recognition rate. In this study, the materials, shapes and sizes of the sensing area have been decided empirically. The optimization of these parameters will emphasize the differences of signals for each letter and it will contribute to the improvement of the recognition rate.

11. Conclusion

In the present work, a wearable sensor system for reading Braille has been developed. The structure of the wearable sensor has been designed to move it over Braille manually. The shape of the waveform is not affected, and the recognition system has been proposed using the characteristics of the waveform. The recognition system divides an input signal into individual signals with almost 100% accuracy as the first process. Multi-layer perceptrons and minimum-distance classifiers were used in the classification process. From the comparison results, the use of the neural classifier shows the better performance that the recognition rate is 75.6%. The developed wearable sensor system has enough potential to recognize Braille. We will improve the architecture of the recognition system to obtain better performance.

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