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OPTIMIZING WEARABLE SYSTEM WITH SEQUENTIAL CLASSIFIER FOR CHILDREN WITH DEVELOPMENTAL DISABILITIES

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Abstract: One of the typical characteristics of children with developmental disabilities is stereotypic behavior, which is the repetition of the same movement. Stereotypic behavior could be a barrier to the social integration of children with developmental disabilities. One efficient key to solving this problem is applying Human Activity Recognition (HAR). In this study, we introduce a method for optimizing a wearable system for HAR. The body part to be analyzed is the finger, the most frequently moved joint, so the wearable device used is a glove with a 2-axis flex sensor and a processor. Since the HAR of this application must continuously be operated, a lightweight system is required. Furthermore, due to the characteristics of a wearable device that operates with a battery, it is essential to implement a long-running system by considering energy consumption and performance. To achieve this, we introduce a lightweight method in all stages from data collection to classifier. We propose a method to improve performance while minimizing the model size by designing Multi-Layer Perceptron (MLP)-based sequential classifier. A sequential classifier is suitable for resolving performance degradation caused by the similarity between gestures. First, classes corresponding to similar gestures are designated as an uncertain group. Then, if the output of the first classifier belongs to the uncertain group, the second classifier with a smaller size classifies it again. Due to the proposed method, higher performance could be achieved than when using a single classifier. As a result of the experiment, it is possible to achieve similar performance with a model with 72% fewer parameters than the optimization design achieved in the previous study.

Keywords: Developmental disabilities; Lightweight Neural Network; Flex sensor; Hand motion Recognition; Human Activity Recognition

1. Introduction

In the case of children with developmental disabilities, there are cases in which stereotypic behaviors, which are constant and regularly repeated, are observed. Therefore, identifying unconscious habit patterns, including stereotypic behaviors, can help improve the behavior of children with developmental disabilities. In this study, we propose a wearable system for Human Action Recognition (HAR). Research in the field of HAR can be divided mainly into two categories. One is an image processing-based technology, and the other is sensor-based. In the case of image processing-based technology, since it uses formalized data called images, it can compare with other technologies objectively, and a huge dataset has been opened. However, it has disadvantages, such as difficulty in detecting small body movements at a distance from the subject. On the other hand, sensor-based systems have a disadvantage because datasets are not opened. After all, the data types vary depending on the application, but are more advantageous in detecting small movements.

The HAR system may use various sensors such as Inertial Measurement Unit (IMU), electromyography (EMG), and flex sensors. Among them, the IMU sensor has a tiny physical size and is suitable for collecting user's physical activity information as it comprises sensors such as an accelerometer and gyroscope. Studies have used it not only for hand gesture recognition [1,2] but also for various physical activities [3-8]. Although it is the most widely used sensor in the HAR field, there are disadvantages in that a large amount of calculation is required for data processing and data may drift due to accumulated errors. EMG sensors have the advantage of measuring small movements of muscles [9-11]. However, it is affected by the condition of the skin surface, such as hair and sweat. Finally, the flex sensor is a sensor that uses the characteristic of changing resistance depending on the degree of bending. It has a simple structure and is resistant to noise, so it is mainly used for sign language recognition [12-14].

Since the body part to be recognized in this study is the finger, a flex sensor is adopted. We design a glove-type wearable device with a 2-axis flex sensor and a processor. The implemented wearable device must be attached to the user's hand and continuously operated. In this study, we introduce a system-level optimization method for implementing a long-running system.

Research on minimizing energy consumption while ensuring a certain level of accuracy has been conducted previously [15]. In this study, Pareto optimization was performed according to the type of processor, the number of parameters of MLP, and the hierarchical structure of MLP. As a result, an energy estimation model was built and optimization was performed at 159 design points. Based on the design optimization factors. In this study, an ensemble-structured sequential classifier is constructed. As a result, higher classification accuracy is achieved with the same number of parameters and calculation execution time.

2. Wearable System Architecture

I. System Diagram

Figure 1 is a system diagram. The sensor used for finger movement detection is a 2-axis flex sensor, designed as a System on a Chip (SoC), and operates by receiving I2C commands. The operating frequency can be set with an I2C command, and the 2-axis angle of the sensor is transmitted in two 16-bit float type. The angle of the x-axis and y-axis, which is the sensor's output, is in the range of -180 to 180 degrees, and the resolution is 0.1 degrees. The processor is activated/deactivated according to the set operating frequency of the sensor. It is an effort to design an efficient long-learning system. For the above reason, the sensor's operating frequency is directly related to energy consumption. Data collection constituting one gesture is performed at intervals of 1 second, and samples collected for 1 second are delivered to the input layer of the MLP through a preprocessing process.

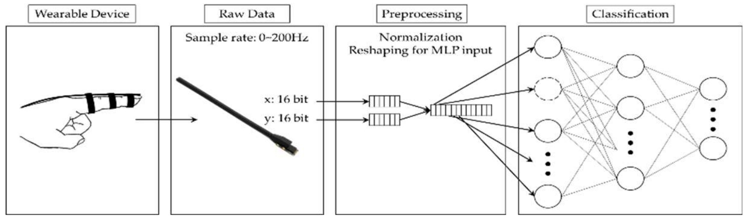

Figure 1: Block diagram of the wearable system

Preprocessing Stage

Since the system to be designed is an embedded system with limited computing resources, an MLP with a simple structure is applied. Since MLP has a fixed input size, preprocessing is required. Figure 2 shows all the preprocessing steps. IIR (Infinite Impulse Response) filtering process to remove the noise of the collected raw data, segmentation process to adjust to a fixed length, and Min-Max normalization process to convert all data features to 0 to 1. Finally, the reshaping process turns the two 1D array data into one 1D array, so the data can be used as the MLP's input layer.

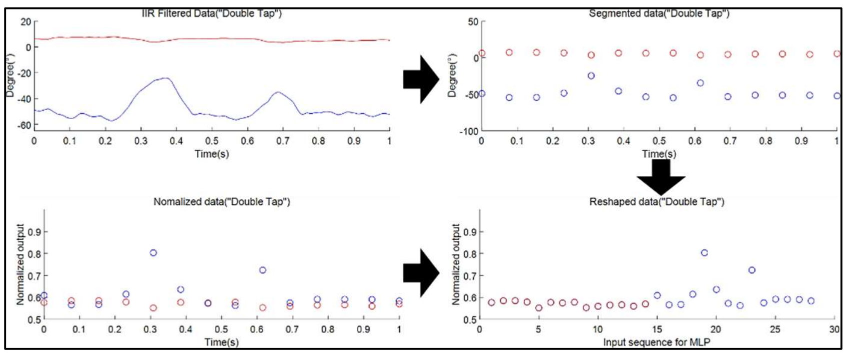

Figure 2: Preprocessing of collected data

1 3. Optimizing MLP Structure

The performance of MLP is determined by various factors, such as the presence or absence of preprocessing, the number of hidden layers, and the number of hidden layer nodes. The performance tends to increase as the number of parameters (model size) constituting the MLP increases, but the relationship between the number of parameters and performance is not directly proportional. After some level, the classification performance is saturated. In other words, an indiscriminate increase in model size does not improve performance and only results in wasted computing resources. For this reason, the optimal MLP structure must be explored through experiments. Figure 3 shows the change in accuracy according to the presence or absence of preprocessing and the number of hidden layers.

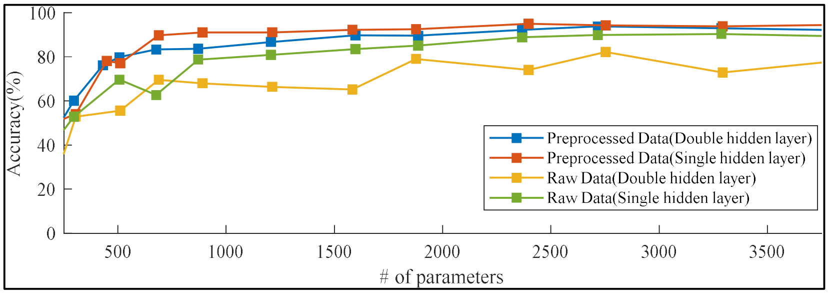

Figure 3:Performance change according to the number of hidden layers and preprocessing.

A. Preprocessed Data vs Raw Data

In this study, the preprocessing process is essential for removing noise, but it is also to fix the length of data to use the sensor output as the input of the MLP. Although, as shown in Figure 3, the performance change according to the presence or absence of preprocessing, regardless of the number of hidden layers, the model trained with preprocessed data (blue, red) always performs better.

II. Single hidden layer vs Double hidden layer

Comparing the performance of MLPs with single hidden layer and double hidden layer in Figure 3, MLPs with a single hidden layer structure show better performance only for preprocessed data. On the other hand, when using raw data as an input of the double hidden layer MLP, the performance increases linearly as the number of parameters increases. Since the role of the hidden layer is to solve a nonlinear problem, the non-preprocessed data has a nonlinear feature.

III. Number of nodes in a hidden layer

All the graphs in Figure 3 shows that the performance improves as the number of parameters increases. However, the performance rapidly improves up to about 900 parameters, and the slope becomes gentle after that. As a result, using the preprocessed input data in a single hidden layer MLP is most suitable for this application. Not only does it show higher performance in all sections, but the performance is rapidly saturated even in small MLP models.

2 4. Proposed Sequential Classifier

In the previous chapter, we explored the performance change according to the presence of preprocessing, the number of MLP parameters, and the structure of the hidden layer. As a result, an MLP classifier with preprocessed data as input and a single hidden layer is most suitable for this application.

In a previous study, an experiment was conducted to build a model that infers the actual energy consumption considering the MCU type, MLP structure, and preprocessing [1].

Figure 4 shows ten Pareto fronts optimized for Pareto between energy consumption and accuracy in the study. Among them, design points specialized in energy consumption (green circle, 28×19×17 structure) and performance-specific design points (blue circle, 100×72×17 structure) are compared. The performance changes up to 91.0% rises steeply depending on the number of parameters. However, it can be seen that about 1.9 times the energy consumption and 9.3 times the parameters are required for a performance improvement of about 4.5% from the next section. Therefore, the 91.0% model is more suitable for implementing the long-learning system in this study, but some performance improvement is required.

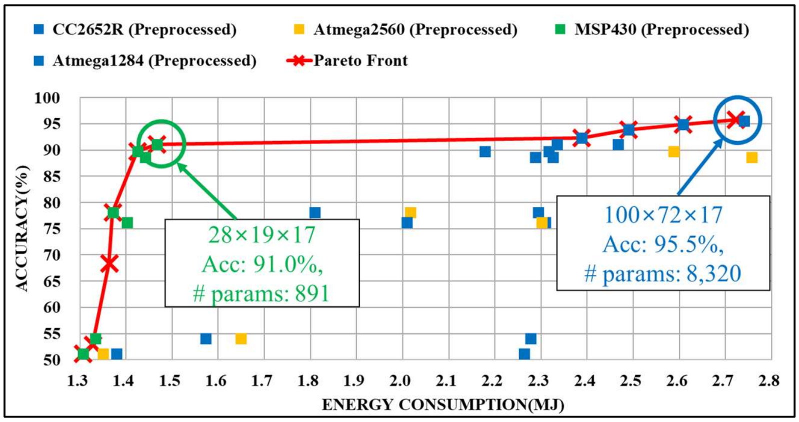

Figure 4:Pareto fronts between energy consumption and accuracy

To solve this problem, we propose a sequential classifier. The proposed sequential classifier does not perform weight update unlike the boosting technique, which is an ensemble learning method. Therefore, it is unsuitable for wearable devices with a limited computing environment. The proposed sequential classifier method designs a small classifier to classify only specific classes with low recognition accuracy. First, it is necessary to determine the class group to be reclassified for this purpose. Figure 5 shows the confusion matrices of the 28×19×17 classifier (a) and the 100×72×17 classifier (b), respectively. As can be seen from both confusion matrices, it can be seen that there are many misclassifications between specific classes.

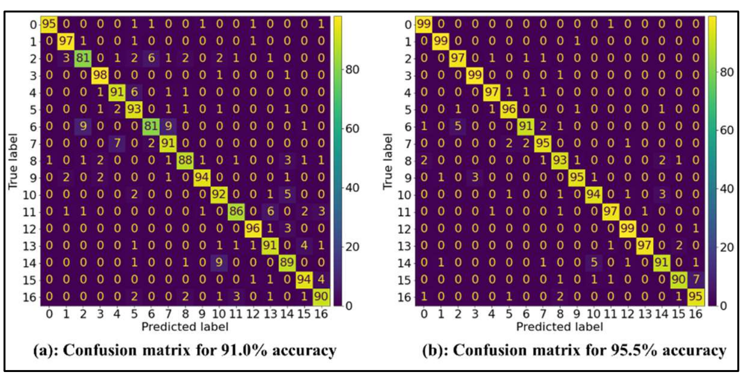

Figure 5:Pareto optimized confusion matrices

Figure 6 shows the raw data of the class with the most misclassification. It is confirmed that a similar data pattern appeared to the human eye. The corresponding six classes are set as uncertain groups, and a small classifier is additionally designed to classify them. The corresponding six classes are selected as targets for reclassification. Based on the evidence confirmed in the experiment in the previous chapter (single hidden layer, application of preprocessing), searching for the number of nodes in the most suitable hidden layer is necessary.

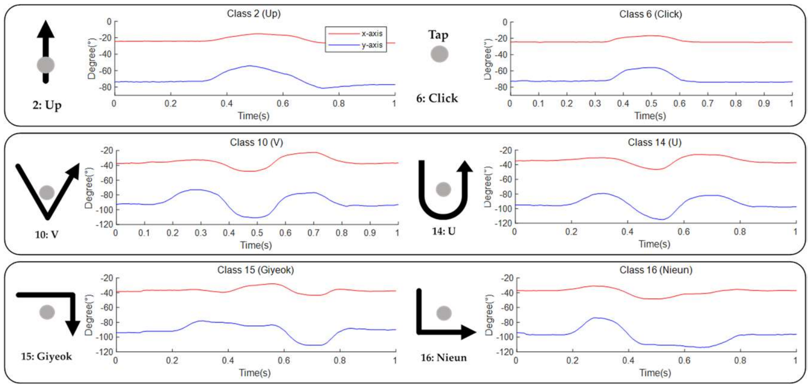

Figure 6:Examples of raw data belonging to Uncertain classes

3 5. Experimental Setup

A. Gesture Definition

This chapter describes the experimental setup. Figure 7 shows the defined gestures. A total of 17 gestures are defined, and composed of pairs of similar or opposite gestures. A start/end position can distinguish by a start/end point of a gesture. Figure 8 is an example of a sequence from start-gesture to end-gesture of “Up”.

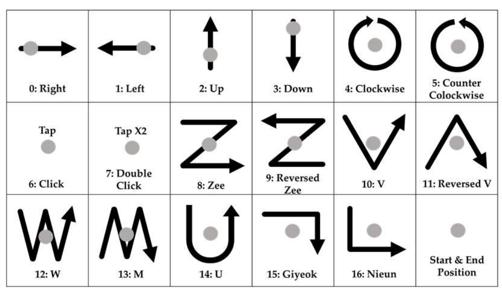

Figure 7:Defined gestures (17 classes).

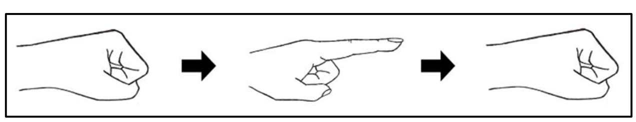

Figure 8: Start-to-end example of one gesture

B. Wearable System Protype

Figure 9 is an example of wearing the implemented system. The Printed Circuit Board (PCB) is designed for miniaturization/light weight of the system. The 2-axis flex sensor of the wearable device is attached onto the index finger and can measure the movement of the finger in two dimensions. The processor used the CC2562R of the Cortex-M4F series which features a clock speed of 48 MHz and a 32-bit RISC structure.

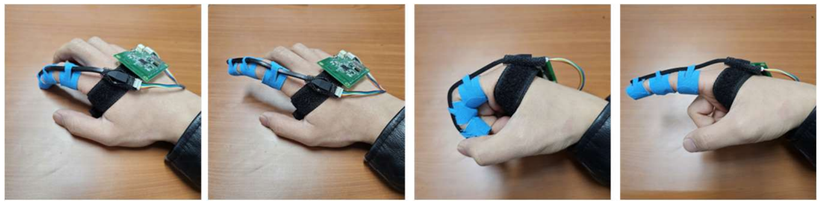

Figure 9:Example of wearing a wearable device prototype

The dataset used in the experiment consists of a total of 17 classes and has 300 samples per class. Samples in the dataset are collected from 5 male and female between ages from 20s to 40s. The training of MLP is conducted in the PyTorch environment, with learning rate of 0.0075 and the maximum epoch to 500. The used activation function is Rectified Linear Unit (ReLU). Those are determined through repeated experiments.

Figure 10 is a Graphic User Interface (GUI) implemented with Matlab for data collection and monitoring. It is an interface between the PC's serial port and the wearable device, and data can be visualized in real time. It makes easier to check if the data is being collected correctly, and to monitor the collected data.

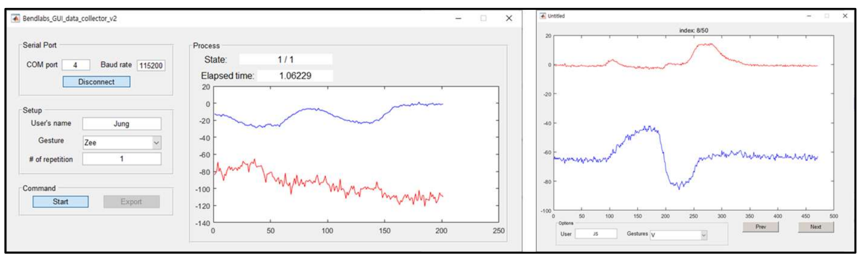

Figure 10:Data collection/monitoring system

C. Designing & Optimizing Sequential Classifier

Figure 11 shows the structure of the proposed sequential classifier. If the output of the first classifier belongs to the uncertain classes, reclassification is performed by a small classifier. The second classifier has fewer parameters than the first because it classifies only six classes corresponding to the uncertain class. Since we already have a Pareto-optimized MLP model between energy consumption and performance, the number of nodes in the input and output layers of the second classifier is determined. However, for optimization design, the number of hidden layer nodes at the point when performance is saturated must be searched. For efficient search, the following two limitations are as follows: It should have fewer parameters than the first classifier, The search second classifier's performance should be higher than the accuracy of the six uncertain classes classified only by the first classifier.

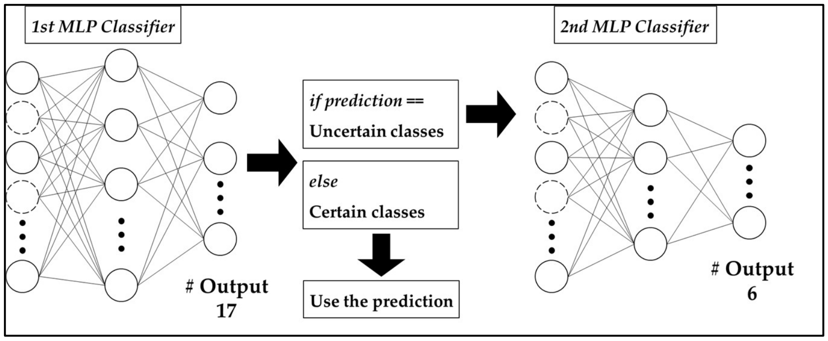

Figure 11:Proposed Sequential Classifier

As shown in Figure 5, the probability that the classifier of the 28×19×17 Pareto-optimized structure classifies the six uncertain classes correctly is 85.8%. The performance of the second classifier must be at least higher than this to achieve performance improvement. As a result of repeated experiments under the above conditions, the most suitable number of hidden nodes is found. Figure 12 shows the result of searching for the optimal number of nodes in the hidden layer.

In Figure 12, the design point at which the performance improvement of the second classifier is saturated is the point where the number of hidden layer nodes is 19 (28×19×6), the accuracy is 95.2%, and the number of parameters is 671. That is, the searched optimal sequential classifier is a combination of the first 28×19×17 classifier (Pareto-optimized) and the second 28×19×6 classifier, and shows a performance of 94.3%. The total number of parameters is 891+671=1562. In the Pareto front shown in Figure 4, 5603 parameters are required to achieve greater than 94.3% accuracy. As a result, applying the sequential classifier, makes it possible to achieve light with a model size of 0.28 times without performance loss.

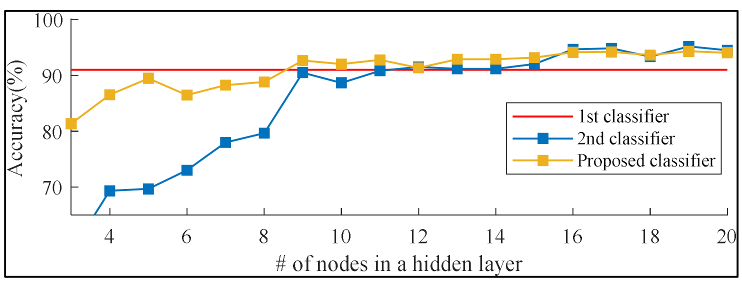

Figure 12:Accuracy change of the 2nd classifier with the number of nodes in the hidden layer.

6. Conclusions

We proposed a wearable system that recognizes and monitors hand gestures among stereotypic behaviors of children with developmental disabilities. Lightweight was achieved to minimize the discomfort felt by users who are children with developmental disabilities and to overcome limited computing resources. Furthermore, by proposing a sequential classifier composed of two MLPs, it was possible to guarantee a certain level of performance while minimizing the use of computing resources. As a result, a high classification accuracy of 94.3% was achieved using minimal computing resources. It is the same as maintaining the accuracy while reducing the model size by about 72% compared to the case where the sequential classifier was not applied.

4 Acknowledgment

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