Shoe Recognition Model with Floor Pressure Sensors

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***Abstract*—In research on traffic flow analysis, computer vision methods using camera images have been the predominant approach. However, using cameras for flow line analysis presents challenges, such as creating blind spots caused by obstructions such as people or objects. Additionally, privacy concerns arise. These issues can be mitigated using floor pressure sensors for flow line analysis. To successfully perform flow line analysis with these sensors, it is essential to identify individuals based on factors such as weight, stride length, speed, and shoe type. In this study, we developed a system to identify shoe types from footprint pressure distribution using a neural network model. Our focus was on three types of shoes: sneakers, room shoes, and sandals. We collected data for each category and created a recognition model, achieving an F-measure of 97.6% in the best model. The primary challenges for practical implementation are measurement time and durability.**

Keywords-Sensors, Neural networks, Flow Line Analysis, Pressure-Sensitive Conductive Sheet.

I. Introduction

Traffic flow analysis in environments such as retail stores, factories, warehouses, and public facilities is crucial for enhancing productivity and mitigating risks. In response to these needs, several image recognition methods using cameras have been proposed in recent years [1]. Although these camera-based methods offer the benefit of using existing surveillance infrastructure, they have considerable drawbacks, including difficulties in detecting overlapping people or objects, which can create blind spots. Additionally, the installation of cameras is often hindered by privacy concerns. However, these challenges can be circumvented using floor pressure sensors as an alternative to cameras, which effectively address both blind spots and privacy issues.

The pressure-sensitive conductive sheet Velostat can be used to create pressure sensors for installation on floors [2]. Velostat has the characteristic of reducing resistance when pressure is applied, allowing for pressure measurements based on changes in voltage. The benefits of Velostat include its low cost, ease of arrangement modifications, high density of measurement points, and excellent portability.

In a previous study on object identification using pressure sensors with Velostat, Yuan *et al.* [3] successfully identified ten different objects, including Lego pieces, a bottle, and an iron block. However, there have been no studies using Velostat-based pressure sensors for flow line analysis.

To perform traffic flow analysis, it is essential to determine whether footprints originate from the same individual. Identifying a person through their footprints involves analyzing various factors, including weight, stride length, walking speed, and shoe type. In this study, we developed a floor pressure sensor using Velostat and a neural network model using sensor data to identify footwear.

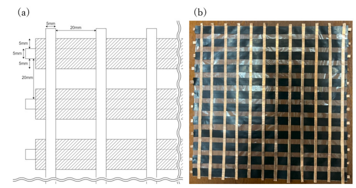

Figure 1. (a) Structure of pressure sensor (b) Created pressure sensor.

The rest of the paper is structured as follows. In Section II, we present the pressure sensor. In Section III, we describe the recognition model. Section IV has the results and discussion. We conclude the article in Section V.

II. Pressure Sensor

The pressure sensors used in this research were constructed using Velostat, copper foil tape, and an Arduino platform.

The sensor we developed has copper foil tapes that are 5 mm wide and spaced 20 mm apart, arranged in a grid formation consisting of 12 tapes both vertically and horizontally, totaling 144 measurement points (Figure 1).

For power transmission, the Arduino's digital pin is directly connected to the copper foil tape aligned parallel to the strip of Velostat. For data reception, the copper foil tape located at the point where it intersects vertically with the strip of Velostat is connected directly to the Arduino's analog pin to measure voltage, which is then linked to ground through a 1 kΩ resistor.

Pressure is measured using the following procedure. First, the Arduino sequentially sends electrical signals to the 12 copper foil tapes positioned parallel to the Velostat. Next, Arduino measures the voltage across all the copper foil tapes on the opposite side while supplying electricity to each individual tape. This process is repeated every 100 ms.

III. Recognition Model

A. Structure of the neural network model

The neural network model used for identification is structured with an input layer, three hidden layers, and an output layer. The input layer takes in raw sensor data, comprising 12 × 12 = 144 nodes. Each of the three hidden layers is a fully connected layer, containing 6 × 6 = 36 nodes. The output layer

Figure 2. Shoes used for data collection.

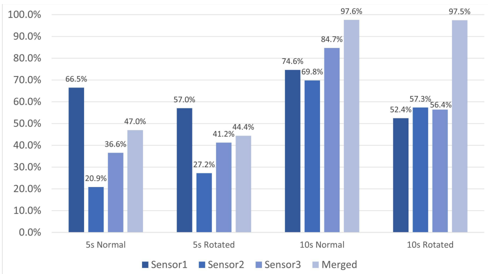

Figure 3. F-measure graph.

generates probabilities for each of the three types of shoes: sneakers, room shoes, and sandals. The model uses Rectified Linear Unit (ReLU) as the activation function for all layers. The optimizer employed is Stochastic Gradient Descent, set with a learning rate of 0.8, whereas the loss function used is cross-entropy loss.

B. Collection of Training Data

Three types of shoes were selected for classification: sneakers, room shoes, and sandals (Figure 2). A 1.5 kg weight was placed inside each shoe.

During the data collection process, the sensor was first calibrated for at least 5 s without any weight. The shoe was then placed on the sensor and allowed to rest for a few seconds before measuring the pressure distribution.

Each shoe underwent this measurement process 50 times, resulting in a total of 150 data points per sensor. Additionally, there were two different waiting times (5 and 10 s) between placing the shoe on the sensor and measuring the pressure. In total, 900 data points were collected, comprising two waiting times and three sensors. We refer to this collection as the normal dataset. We also created a rotated dataset by rotating the normal dataset 90, 180, and 270 degrees. Furthermore, we created a merged dataset that consolidated the data without differentiating between sensors.

The collected data were split into training, validation, and test sets with a random distribution. The ratio for all datasets is 70:15:15.

IV. Results And Discussion

Figure 3 shows the F-measure for each dataset.

During a waiting period of 10 s, both normal and rotated measurements exceed 5 s. Possible reasons for this include unresolved noise, such as vibrations generated when the shoe is placed on the sensor, which may not dissipate in 5 s, and insufficient power from the Arduino, which can delay voltage recovery.

For each sensor, measurements under normal conditions during the 10-s waiting period were higher than rotated data. This occurs because the sensor's sensitivity characteristics become more pronounced over time. While the model can estimate sensitivity bias using normal data, it struggles with data from rotated measurements. Factors contributing to this biased sensitivity may include non-uniform resistance of the Velostat, errors in sensor fabrication, and degradation from use.

This sensor has been designed primarily for traffic flow analysis. In practical traffic flow analysis, multiple sensors will be deployed, making it impractical to retrain the model with each new sensor. Therefore, using the rotated data method for data collection is advantageous because it mitigates the risk of sensor sensitivity bias and facilitates an easy increase in the training dataset.

V. Conclusion

In this paper, we developed a pressure sensor using a pressure-sensitive conductive sheet called Velostat coupled with a neural network model to identify different types of shoes. We performed experiments with three different shoe types. The trained model achieved an impressive F-measure of 97.6%. Using a rotated dataset proved to be the most effective approach for real-world applications because it involved rotating the data every 90 degrees, thereby eliminating sensitivity bias from each sensor.

The following challenges may arise when performing an actual flow line analysis. In this study, experiments were performed using 1.5 kg weights placed inside the shoe. However, the pressure readings could surpass the measurable range when an individual walks on the sensor. To obtain accurate pressure distribution, measurements were recorded several seconds after placing the shoe on the sensor. However, this waiting period is not practical in real-world analyses. Additionally, while this research used three different types of shoes, there are many more types in reality, some of which are more difficult to identify.

To address the issues identified in this research and improve our responses to projected situations, we will further develop the following sensors and applications: a sensor with improved response time and durability, a system capable of managing multiple sensor errors, and a system that can identify individuals based on various feature values.

References

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