2025 IEEE World Haptics Conference (WHC)
Suwon Convention Center, Suwon, Korea
July 8 ~ 11, 2025

Perception System using Heat and Vibration Sensor for Liquid Classification with Customized 1D-CNN

Hyunjun Park[1] and Youngsu Cha[2,†], *Senior member*, IEEE

I. Introduction

Recent robotics advancements have accelerated the development of intelligent manufacturing systems [1]. Therein, object recognition with visual sensing plays a critical role [2]. In parallel, tactile sensing inspired by human receptors has also emerged for classifying objects through direct contact [3]. However, liquid classification in containers remains an untapped region due to the optical transparency of liquids [4].

Here, we introduce a perception system on robotic fingers with machine learning for classifying liquids in bottles. Specifically, the system integrates sensations of thermal conduction and frequency response, inspired by human thermal and vibrational receptors. Additionally, a one dimensional convolutional neural network (1D-CNN) with dual parallel structure is employed to process the multimodal input. This biologically inspired approach offers a solution for liquid classification with broad application in robotic perception.

II. System Description

A. Sensor Configuration

The configuration of the heat sensor module was shown in Fig. 1 (a). The heat sensor module used a thermoelectric device (TED), operated based on the Peltier effect. With this effect, the TED from a voltage input could generate heat, thereby inducing temperature variations between the heat sensor module and a contacted object. Additionally, a resistance temperature detector (RTD) was used in the heat sensor module to measure the temperature variations. The RTD could detect temperature variations measuring voltage outputs resulting from the linear resistance changes. The TED and RTD were affixed together with a polyethylene terephthalate (PET) tape and silicone finger cot. The heat sensor module formed a compact sensing unit capable of generating and detecting temperature variations during contact.

This work was supported by the National Research Foundation of Korea (NRF) Grant funded by the Ministry of Science and ICT (MSIT) (RS-2022-NR067595). (†Corresponding author: Youngsu Cha)

[1]H. Park is with the department of Smart Convergence, Korea University, 145 Anam-ro, Seongbuk-gu, Seoul 02841, South Korea. e-mail: jetk2634@korea.ac.kr

[2]Y. Cha is with the school of Electrical Engineering, Korea University, 145 Anam-ro, Seongbuk-gu, Seoul 02841, South Korea. e-mail: ys02@korea.ac.kr

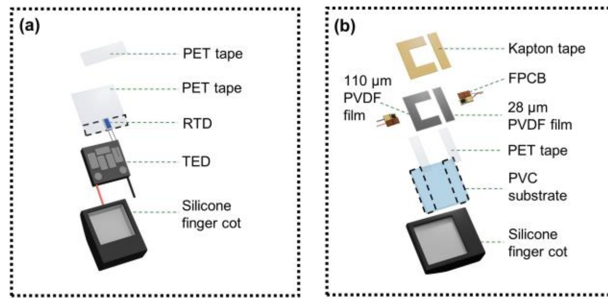

Fig. 1. Configuration of **(a)** heat sensor module, and **(b)** vibration sensor module.

The configuration of the vibration sensor module was shown in Fig. 1 (b). The vibration sensor module was operated based on piezoelectric effect. The module consisted of an actuator and a sensor, employing a 110 μm polyvinylidene fluoride (PVDF) for actuator and a 28 μm PVDF film for sensor. The actuator and sensor films were cross-attached to one side of a customized flexible printed circuit board (FPCB). Both films were covered with a kapton tape, and attached to a polyvinyl chloride (PVC) substrate using PET tape and silicone finger cot. The vibration sensor module could capture different frequency responses as liquid through piezoelectric interaction between the actuator and sensor.

B. Neural Network

The 1D-CNN model was utilized to classify objects. The model was customized to dual parallel to handle multimodal properties (Fig. 2). The feature learning part was composed of an input layer, two convolution layers, and two pooling layers of each model. The outputs from two models were flattened and concatenated in to unified vector. This merged data was then fed into a dense layer, and the other dense layer was with a softmax activation function. This dual parallel architecture enabled effective integration of multimodal tactile data and facilitated accurate liquid classification.

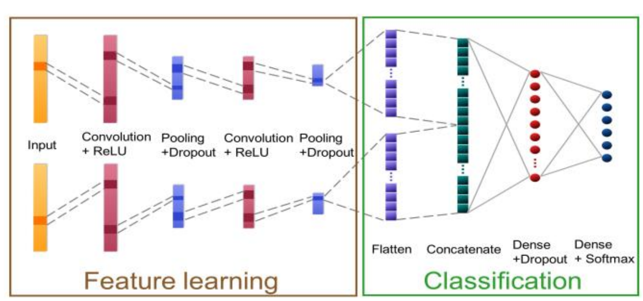

Fig. 2. The flow chart and structure of the dual parallel 1D-CNN-based classification model.

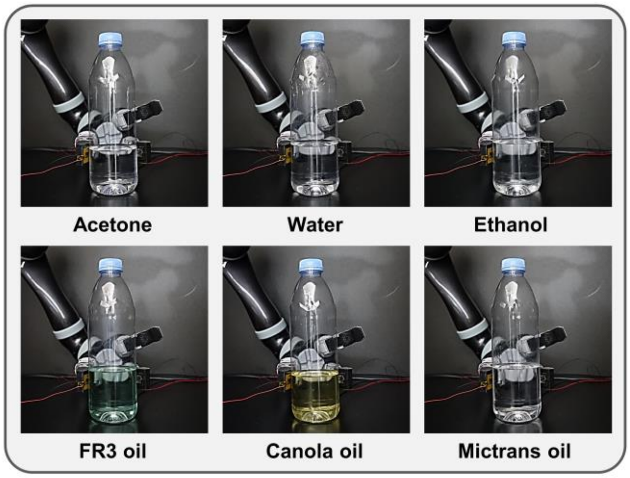

Fig. 3. Pictures of grasping bottles containing acetone, water, ethanol, FR3 oil, canola oil, and mictrans oil respectively.

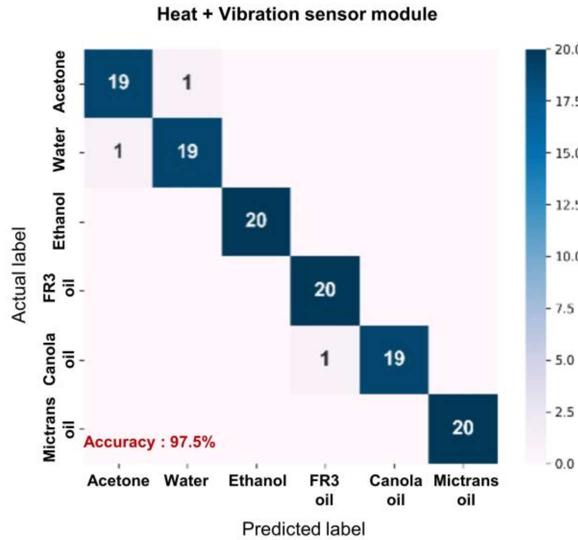

Fig. 5. The confusion matrix using multimodal tactile sensor system with heat and vibration sensor module.

III. Experimental Results

To classify the liquid types, six identical PET bottles were filled individually with 200 mL of acetone, water, ethanol, FR3 oil, canola oil, and mictrans oil (Fig. 3). The bottles were grasped with two parallel fingers, left for the heat sensor module and right for the vibration sensor module. Each bottle was grasped 200 times, resulting in 200 data sets per sensor module for each liquid.

The total average temperature decrements recorded by the heat sensor module were presented in Fig. 4 (a). The temperature decrements were differed by two group: one comprising acetone, water, and ethanol, and the other comprising FR3 oil, canola oil, and mictrans oil. The first group showed average temperature decrements exceeding 1.4 ℃, while the second group's decrements were below 1.4 ℃. The average frequency responses of the vibration sensor module were shown in Fig. 4 (b). Despite similarities in overall frequency response patterns, the average peak amplitudes divided distinctly as two groups. The first group containing acetone, water, and ethanol exhibited higher average peak amplitudes (> 1.4 mV). The second group containing FR3 oil, canola oil, and mictrans oil displayed lower amplitudes (< 0.5 mV). These results suggested that temperature decrements and frequency responses were differed to classify liquids.

The 200 data sets from each liquid type were divided randomly into training, validation, and test sets with the same 8:1:1 ratio. Each dataset was individually normalized between 0 and 1 using separate min-max scalers for each sensor module. The proposed system with the dual parallel 1D-CNN model attained significantly classification accuracy (97.5 %) shown in Fig. 5. By integrating both sensing modalities, the perception system enhanced the classification resolution while merging their respective superiorities. The system, using the dual parallel 1D-CNN, captured both thermal and mechanical features of each liquid.

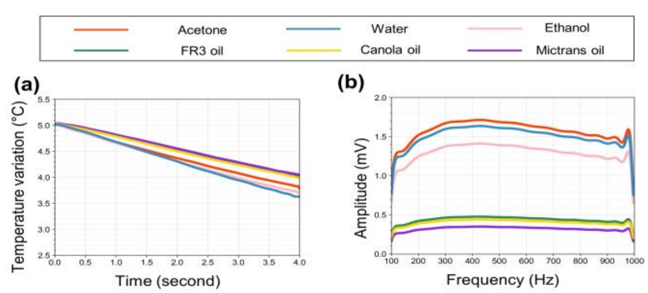

Fig. 4. Entire average data of each type using (a) heat sensor module and (b) vibration sensor module.

IV. Conclusion

In this study, we proposed a perception system with dual parallel 1D-CNN for liquid classification based on a unified system enabling multimodal integration of temperature variation and frequency response. The developed system consisted multimodal tactile sensor system and optimized machine learning process. The proposed system achieved a remarkable accuracy of 97.5% for liquid classification. The experimental results highlighted the promising potential of utilizing perception system within intelligent robotic grippers for liquid classification.

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