Surface Detection by an Artificial Finger Using Vibrotactile Recognition

Alhussein Mohamed Hazem Osman[1], Alireza Abbasimoshaei[1], Fady Youssef[1], Thorsten A. Kern[1]

***Abstract*— This paper presents a method for an interactive surface recognition system using a robot and a vibrotactile sensor interacting with different surfaces by performing scratching movements on each of them. Surface classification models were developed by extracting statistical features of the vibrations detected by the accelerometer using four machine learning algorithms and making a comparison between them.**

I. Introduction

Service robots are increasingly in demand in a variety of fields, which has driven the development of better sensing and manipulation capabilities. While most research has focused on visual object identification, the use of tactile feedback could help robots handle objects and perform tasks more effectively. [1]. Research has shown that there is a tactile modality for encoding rough surfaces and a vibrotactile modality for smooth surfaces [2].

The research is motivated by studies that have consistently shown that exploratory behaviors are crucial in different fields [3]. This paper discusses the use of a metal finger with a mounted accelerometer to detect vibrations in the finger while a robot scratches different surfaces to detect and classify them by using different machine learning algorithms.

II. Experimental Setup

The robot used in the experiments and the overall experimental setup are shown in Fig.1. The robot model is a UR10e developed by Universal Robotics. A metal rod simulating a finger is attached as the end effector of the robot, to which a 3-axis accelerometer, a Triaxial ICP®Model HT356A44 from PCB Piezotronics with a resolution of 0.001 m/s^2rms and a frequency of up to 10 KHz, is mounted. The scratching behavior was performed by sliding the robotic fingertip over 10 different material surfaces at a speed of 20 mm/s over a distance of 200 mm. The scratch behavior was performed 25 times on each surface, resulting in $25 * 10 = 250$ trials.

On average, across all trials and data, the Neural Network algorithm outperformed the *k*-NN algorithm by about 10%. The *k*-NN algorithm was the least accurate classifier. Among all the other classifiers, *k*-NN is the easiest to implement and tune. So, it is important to check the parameters such as accuracy and recognition speed for each application and then choose the most suitable method. Moreover, all three traditional machine learning classification algorithms showed very similar accuracies in surface recognition, proven on our tests on other datasets (TABLE I). Compared to the Neural Network classifier, they required less time to train. However, there is still much room for improvement.

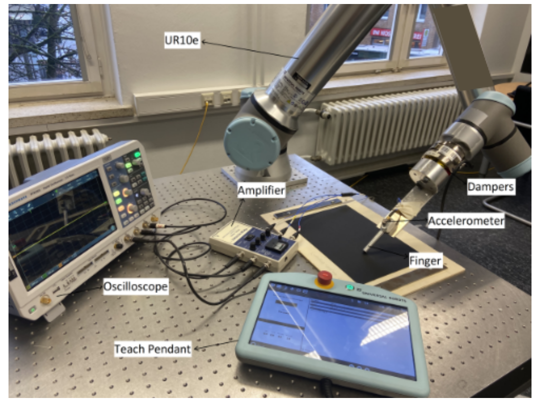

Fig. 1. Experimental setup.

TABLE I
ACCURACY OF CLASSIFICATION ALGORITHMS ON DIFFERENT DATASETS

Algorithm	Developed dataset	Penn haptics	LMT haptics
K-NN	74.7%	35%	88.5%
SVM	75.1%	46%	88.75%
Random Forest	76.25%	48%	91.5%
Neural Network	84.9%	47.5%	92.5%

III. Conclusion

One of the main results of this study is to investigate how different classification algorithms perform on problems with multiple classes. In this work, results have shown that using a Neural Network for classification provides more accurate results but also requires more time, memory and processing power, which may be limited in many cases. It has also been shown that classical machine learning algorithms can produce acceptable results. In any application, the needed algorithm depends on the available resources and priorities.

Extraction of additional features from the accelerometer, such as evaluation of the softness of the materials, and tests with additional material should be performed for future work.

References

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[1]The auhors are with the Institute for Mechatronics in Mechanics, Hamburg University of Technology, Hamburg, Germany e-mail: (al.mohamed.hazem.osman, al.abbasimoshaei, f.youssef, t.a.kern)@tuhh.de