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Surface Recognition Using Dash Robot

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Abstract: Understanding the situation around the system has been an important issue for both military and civilian applications. As a part of situation awareness, this paper focuses on surface recognition for the mobile agent so that the system can identify where it was placed. In this paper, we used a small, lightweight, hexapedal robot with an integrated sensor, such as an accelerometer and a gyroscope. Five different types of surfaces are tested and supervised learning methods are applied for classification.

Keywords: Surface recognition, Mobile robots

1. INTRODUCTION

Situation understanding using various sensors has been attracting topic in broad area. A good example is smart-phone; there exists significant number of applications to discover contexts about the users and their surroundings to provide betters services to them. In robotics, a localization method including simultaneous localization and mapping (SLAM) has been extensively studied, and becomes a central part of robotic applications such as autonomous driving and navigation. Using sensors such as laser scanner and camera, various existing works successively solve localization problem [1], [2]. However, solving the localization problem is computationally difficult and requires the use of costly sensors so that it is not suitable for the entire robot platform. In this work, we consider the problem of surface recognition that can be applicable to low-cost robot platform. Although knowing what type of surface contains less information than location, it remains valuable and useful for the specific situation.

The main robot platform in our work is off the shelf robot which is small, lightweight, and 6-legged [3] (Figure 1). The similar robot design was first introduced in the previous work [4] which is called *DASH*, which consists of rigid links and polymer hinge elements to transfer energy from the single motor to the legs. Unlike [4], our dash robot is controlled by two DC motors and each motor controls the movement of the three connected legs, allowing a more flexible control in several directions.

Our work is based on the previous work [5], which presents an efficient surface recognition algorithm for the smart-phone device. [5] uses only a small subset of the most informative features of accelerometer readings with feature selection to reduce computation time. In this work, the main device is switched from smart-phone to the dash robot with a different feature design.

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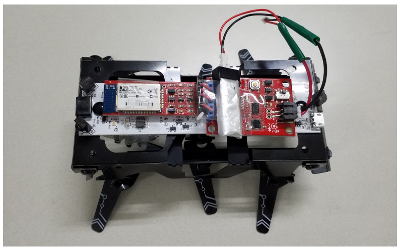

Fig. 1 Dash robot with an attached sensor device.

2. APPROACH

A core of our work is extraction of features from data and training classifiers. We collect signal inputs from a sensor device attached at the dash robot, and extract features from the data. From the obtained features, classical supervised learning approaches are applied to train classifies.

2.1 Feature Extraction

For a classification problem, feature extraction is critical that can influence the performance of classifiers. If non-informative features are used, significant errors may occur. In [6], a feature set which consists of 24 time domain and frequency domain features are used for mobility recognition. In this work, features are extracted only from frequency domain due to high noise occurred in the dash robot. An input signal in the specific time range is converted in to the frequency domain by a fast Fourier transform (FFT). In the frequency domain, the spectrum is evenly dived into five sub-bands B_1, B_2, B_3, B_4, B_5. An average magnitude in each sub-band is drawn into feature so that generated feature can well represent the dominant frequency of the input signal. Figure 2 shows feature extraction for a given input sensor data.

2.2 Classifiers

Two classifiers are tested for surface recognition.

2.2.1 k-NN classifier

A k-nearest neighbor (k-NN) classifier classifies a test data with respect to a majority vote of nearby training

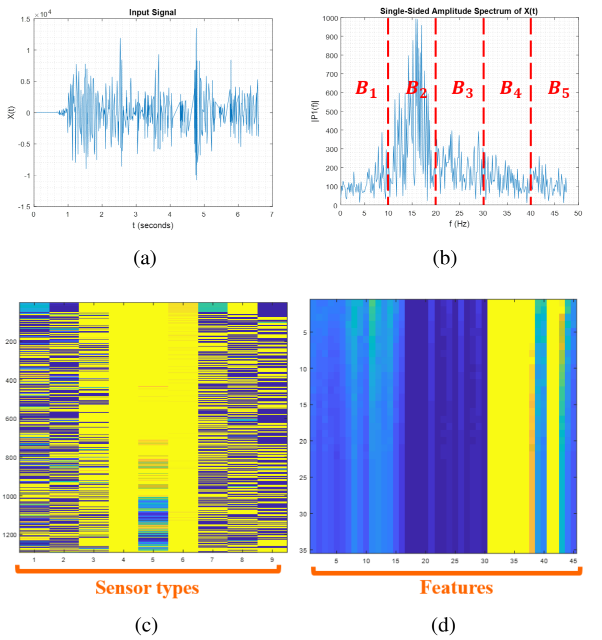

Fig. 2 Feature extraction for input sensor data. (a) Sensor input in time domain. (b) Sensor input in frequency domain. $B_1, ..., B_5$ refer sub-bands. (c) Visualization of raw sensor data. (d) Visualization of extracted features.

data points. The class label for the new data is the class with the largest number of training data points form k nearest training data points.

2.2.2 SVM classifier

A support vector machine (SVM) is an nonparametric classification algorithm [7]. For a binary classification problem, an SVM searches the separating hyperplane with the largest margin so that it can result the smallest generalization error. A set of SVM classifiers is used for multi-class classification problems; Single SVM classifier distinguishes a specific labeled data in one-versus-all manner.

3. EXPERIMENT

We conducted experiments in the installed testbed with 5 different surface types (Figure 3). A 9-DOF IMU board with three sensors is attached to the dash robot: ITG-3205 (triple-axis gyro), ADXL345 (triple-axis accelerometer), and HMC5883L (triple-axis magnetometer). During data collection procedure, a robot is controlled with a non-skewed control input in order to make the acquired sensor data not to be sensitive to the control input.

A single feature with 45 dimension is extracted from input signals of 2 seconds. After converted into frequency domain, we reject part of spectrum greater than 50 Hz. For k-NN classifier we set k as 10.

Classification results are shown in Table 1, which shows correction ratio for each type of surface. In average, both classifiers show correction ratio larger than 70% (k-NN: 73.1%, SVM: 78.5%). However, it can be noticed that SVM classifier shows better classification performance than k-NN. While the k-NN classifier has little recognition capability on particular surface types, the SVM classifier shows relatively even performance on all types of surfaces.

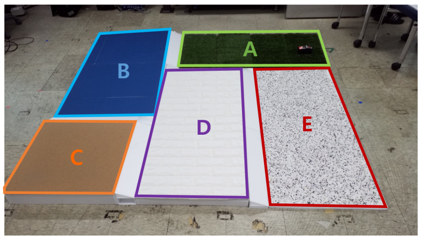

Fig. 3 Experiment environment with 5 different surface types: (A) grass, (B) corrugated cardboard, (C) plywood, (D) plastic bricks, (E) rocks.

Table 1 Classification results (percentage)

Type of surface	A	B	C	D	E
Score (k-NN)	14.3	94.6	89.8	39.6	96.4
Score (SVM)	100	71.4	72.2	77.7	82.7

It seems that there is some margin to improve performance in the future work, which can be achieved by feature selection to remove meaningless features using mutual information and principal component analysis. Also a recent classification method such as deep-learning can be applied.

REFERENCES

[1] G. Dissanayake, H. Durrant-Whyte, and T. Bailey, “A computationally efficient solution to the simultaneous localisation and map building (SLAM) problem,” *Proc. of the IEEE International Conference on Robotics and Automation*, pp. 1009-1014, 2000.

[2] F. Endres, J. Hess, N. Engelhard, J. Sturm, D. Cremers, and W. Burgard, “An evaluation of the RGB-D SLAM system,” *Proc. of the IEEE International Conference on Robotics and Automation*, pp. 1691-1696, 2012.

[3] http://kamigamirobots.com

[4] P. Birkmeyer, K. Peterson, and R. S. Fearing, “DASH: A dynamic 16g hexapedal robot,” *Proc. of the IEEE/RSJ International Conference on Intelligent Robots and Systems*, pp. 2683-2689, 2009.

[5] J. Cho, I. Hwang, and S. Oh. “VibePhone: efficient surface recognition for smartphones using vibration,” *Pattern Analysis and Applications*, pp. 251-265, 2016.

[6] H. Lu, J. Yang, Z. Liu, N. D. Lane, T. Choudhury, and A. T. Campbell, “The Jigsaw continuous sensing engine for mobile phone applications,” *Proc. of the International Conference on Embedded Networked Sersor Systems (SenSys)*, pp. 71-84, 2010.

[7] C. J. C. Burges, “A tutorial on support vector machines for pattern recognition,” *Data mining and knowledge discovery*, pp. 121-167, 1998.