Demo: Unsupervised Fill-level Estimation for Smart Trash Removal Systems

Yiran Zhao, Shuochao Yao, Shen Li, Shaohan Hu, Huajie Shao, Tarek Abdelzaher
Department of Computer Science
University of Illinois at Urbana-Champaign
{zhao97, syao9, shenli3, shu17, hshao5, zaher}@illinois.edu

Abstract

In this demo, we show an unsupervised, non-intrusive fill level estimation system, called Smartbin, which can be easily installed on the outside surface of waste bins to measure their occupancy levels. Smartbin uses a cheap mini-motor that exploits the physical nature of vibration resonance by learning forced vibration characteristics of the bin at different fill-levels over a small number of garbage collection cycles. This learning process occurs in a completely automated fashion ultimately enabling accurate fill level estimation that can serve as a component of smart (e.g., demand-based) trash removal services. A preliminary evaluation on six different waste bins demonstrates ability of the system to accurately measure empty, half-full, and full bin states. This physical system will be demonstrated to illustrate unsupervised learning and fill level estimation.

Keywords

Internet-of-Things, Smart Home, Waste Management

1 Introduction

The increasing popularity of Internet-of-Things (IoT) sensing systems brings about unprecedented opportunities to enable a variety of new services for monitoring and control in smart cities. Measuring waste bin fill-levels is one such service. It helps building operators schedule garbage collection more responsively and optimize the quantity and location of waste bins. Existing systems [3] measure physical quantities of garbage, such as weight, height, volume, or appearance (images), which requires careful installation, calibration and/or manual labeling. In contrast, Smartbin indirectly measures fill-level by sensing changes in motor-induced vibration features on the outside surface of waste bins. It operates in an entirely unsupervised manner to develop a fill-level classifier within a short period of time, thereby enabling accurate fill-level measurements, as we show in this demo.

International Conference on Embedded Wireless
Systems and Networks (EWSN) 2017
20–22 February, Uppsala, Sweden

ISBN: 978-0-9949886-1-4

2 System Description

As shown in Figure 1, the main component of Smartbin is a Particle Photon platform that is Wi-Fi enabled. The Photon device is stacked on a SparkFun LSM9DS1 IMU shield, which has a 3-axis accelerometer. A mini vibration motor is connected to the DAC output pin on Photon. The whole system costs about \$60, which is well within the price range of typical smart home automation systems, and is powered by a 3.7V 2000mAh battery that can last for up to 2 months.

Smartbin exploits the underlying physics, where increasing bin fill-level will change not only the mass of garbage but also its resonant vibration frequency and damping coefficient. To indirectly measure such physical quantities, the Smartbin device wakes periodically and linearly increases the voltage (V) on the motor to find the vibration resonance point, where the intensity (I) is maximum, then goes to sleep. As the bin fills up, the resonance voltage and maximum vibration intensity change. Smartbin periodically sends the found resonance points (i.e., pairs of voltage and intensity maxima $\{(V_i, I_i), i = 1, 2, ...\}$) to a server. The server runs our algorithm to learn recurring vibration features and map them to fill levels, ultimately enabling fill-level estimation.

More specifically, given a collection of recent samples, the learning algorithm on the server first clusters them by calculating a similarity metric based on a custom distance function. A K-means algorithm [4] is used to cluster the samples, based on the resulting pairwise sample distances, into 3, 6, or 9 clusters. An optimal number of clusters is then chosen automatically for the bin at hand based on the quality of clustering for different K. Namely, we choose K for which the average ratio of intra-cluster distances to inter-cluster distances is minimized. The boundaries between different garbage collection cycles are detected by finding the

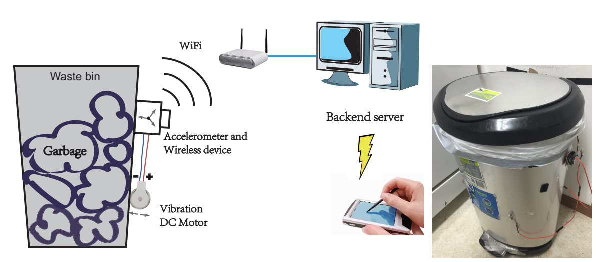

Figure 1: System architecture and hardware installation.

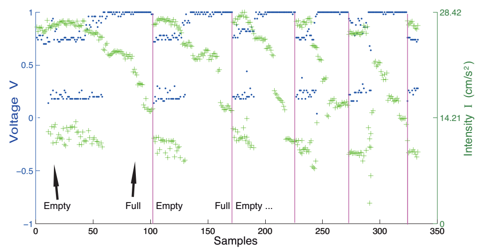

Figure 2: Raw samples.

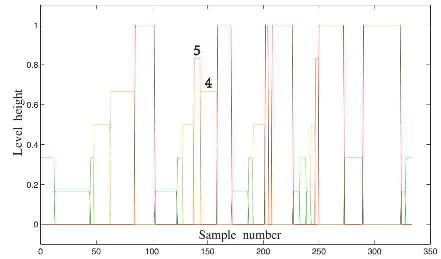

Figure 3: Cluster into 6 levels.

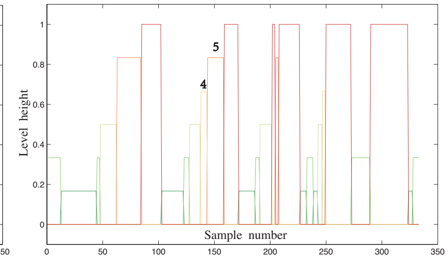

Figure 4: Reorder the levels.

point where the level jumps from full to empty. It corresponds to finding temporally adjacent clusters that are maximally dissimilar, labeling them full and empty, respectively (in chronologic order). In between cycle boundaries, garbage levels are assumed to increase monotonically, which offers a way to label the remaining clusters, reflecting the ascending level trend in each cycle. Next, representative samples are selected from the resulting automatically labeled clusters. Estimation of empty, half full, and full states is then based on matching a new sample to the most similar set of already labeled samples. We find that 3 cycles are enough to deliver accurate measurements.

For example, the collection of samples shown in Figure 2 are clustered into 6 clusters (Figure 3). The garbage collection cycle is detected by finding the point where the level jumps from full to empty. The cluster with the highest intensity is assigned level 1 and the one with the second highest intensity is assigned level 2. They constitute the empty state. Similarly, the clusters with the lowest and second lowest intensity are level 6 and 5, respectively, and they constitute the full state. After cycle detection, the level IDs are adjusted to better reflect the ascending trend in each cycle (such as by exchanging level 4 and 5 in Figure 4).

3 Results

In preliminary evaluation, we installed Smartbin on 6 waste bins of different sizes. After three garbage collection cycles, we ran our algorithm to process the samples. For testing purposes, we manually filled the waste bins to approximately empty, half full and full states, taking around 100 samples at each state. The confusion matrix of the 3 states was computed. We calculate the F1-score to measure classification accuracy. The average F1-score of the 3 states across all 6 waste bins is 0.9, and the F1-score of detecting full state is 0.92. We do find out that bigger bins show more accuracy than smaller ones. For big waste bins, the average F1-score is 0.95. For small waste bins, it is 0.85. We think that this is because the damping effect for bigger bins is more significant.

An advantage of our system is that measurements of the full state remain accurate even when the bin is filled with light-weight garbage such as empty bottles, cans and cartons. For methods based on weight [1], a full bin of light-weight garbage may only measure 13% of the normal full-state weight, leading to poor measurement results. Computer vision based methods [2] can solve this problem but they do not work well if there is a lid on the bin. For our system, the average F1-score of measuring full state with *light weight garbage* is as high as 0.8. A more detailed explanation of system operation and underlying principles is deferred to a concurrent full-length paper.

4 Demo Scenario

In the demo, we will choose waste bins from the conference site or local market, install the device and use a laptop as the backend server. The audience will throw objects of different weights and sizes into our waste bins. Once a bin gets filled, it is emptied. A laptop will show samples collected on the server, as well as results of clustering. After manual emptying has occurred for a few times, the learning algorithm classifies the different clusters. Subsequently, when the audience throw objects into the bin, the server will classify the resulting fill-level into empty, half full, or full, presenting it on the laptop or a mobile device. We will also fill the bins with empty cans or bottles to prove that light-weight garbage can still be accurately accounted for.

5 Conclusions

We demonstrate Smartbin, a vibration-based waste bin fill-level measurement system. It leverages a cheap vibration mini motor and an off-the-shelf accelerometer to find the vibration features of the waste bin as it fills up. Smartbin learns from historical samples in a completely unsupervised manner, and provides accurate measurements quickly. Compared to other systems, Smartbin is cheap, non-intrusive, free of calibration or labeling, and can incrementally augment existing bins. It can also be accurate in the presence of lightweight garbage such as empty cans and bottles.

6 Acknowledgments

This work was supported in part by NSF grants CNS 16-18627, CNS 13-20209, CNS 13-29886 and CNS 13-45266.

7 References

[1] M. A. Al Mamun, M. A. Hannan, A. Hussain, and H. Basri. Integrated sensing systems and algorithms for solid waste bin state management automation. *IEEE Sensors Journal*, 15(1):561–567, 2015.

[2] M. Arebey, M. Hannan, R. A. Begum, and H. Basri. Solid waste bin level detection using gray level co-occurrence matrix feature extraction approach. *Journal of environmental management*, 104:9–18, 2012.

[3] M. Hannan, M. A. Al Mamun, A. Hussain, H. Basri, and R. A. Begum. A review on technologies and their usage in solid waste monitoring and management systems: Issues and challenges. *Waste Management*, 43:509–523, 2015.

[4] G. F. Tzortzis and A. C. Likas. The global kernel-means algorithm for clustering in feature space. *IEEE Transactions on Neural Networks*, 20(7):1181–1194, 2009.