Poster: VibroScale: Turning Your Smartphone into a Weighing Scale

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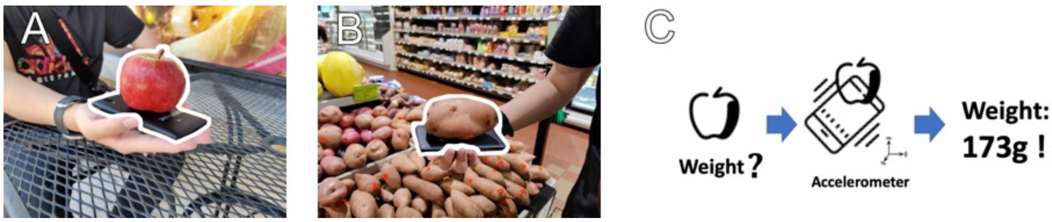

Figure 1: Use case of VibroScale weighing food items (A) in food courts and (B) in grocery stores. (C) System overview.

ABSTRACT

Smartphones, with their ubiquity and plethora of embedded sensors enable on-the-go measurement. In this poster, we describe one novel measurement potential – weight measurement – by turning an everyday smartphone into a weighing scale. We describe VibroScale, our vibration-based approach to measuring weights of objects, that are small in size. Being able to objectively measure the weight of objects in free-living settings, without the burden of carrying a weighing scale has several possible use cases, particularly in weighing of small food items. We designed a smartphone app and regression algorithm that estimates the relative induced intensity of an object placed on the smartphone. We tested our proposed method on more than 50 fruits and other everyday objects of different sizes and weights. The results demonstrate that our smartphone-based method can measure the weight of fruits without relying on an actual weighing scale. Overall, we observed that VibroScale can measure one type of object with a mean absolute error of 12.4 grams and a mean absolute percentage error of 7.7%. We believe that in future this approach can be generalized to estimate calories and measure weight of various types of objects.

CCS CONCEPTS

• **Computer systems organization** → **Sensor networks**; **Robotics**; *Redundancy*.

KEYWORDS

Smartphone; Mobile Application; Weighing Scale; Automatic Measurement; Vibration; Accelerometer; Food Weight Estimation; Fruit Calorie Estimation; Ubiquitous Computing

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1 INTRODUCTION

In order to objectively quantify characteristics of an object, it is necessary to measure the object. Often specific devices are necessary to make these measurements – e.g., a weighing scale is necessary to measure weight. However, it is burdensome to carry these measuring devices at all times. With the advancement in mobile and ubiquitous computing, researchers have explored performing these measurements using various types of everyday devices; one such device is the smartphones. Modern smartphones are equipped with several sensors, which can support various types of measurements. Smartphone-based measurements can range from human activities [8], and mood [9] measurement to physical measurement of liquid's surface tension [17] or elevation [11]. Researchers, while performing these measurements, have explored approaches that utilized various smartphone's components and sensors.

Among the various components and sensors in the smartphone, in this paper we focus on using the accelerometer sensor (that commonly measures the smartphone's acceleration) and the smartphone's vibration motor (that is commonly used to provide haptic feedback). We hypothesize that the vibration caused by a smartphone's vibration motor is different when a weight is placed on the smartphone, as compared to when no weight is placed on the smartphone. In this paper, we present *VibroScale*, a system that explores the change in vibration when a weight is placed on the smartphone. The working of VibroScale is shown in Figure 1. Specifically, VibroScale controls the vibration of the smartphone's vibration motor and measures the amplitude of the vibration with the smartphone's built-in accelerometer. Indeed, as shown in Section 4, not only does a weight placed on top of the smartphone dampen the vibration (as captured by the accelerometer), but the dampening is linearly correlated to the amount of weight placed on the smartphone. Overall, we observed that using a smartphone, we could measure a wide range of weights.

However, while realizing VibroScale, we identified several challenges: (i) The vibration pattern is affected by the placement of the item on the smartphone. The object should exert its weight completely on the smartphone, and should not touch other surfaces. (ii) Every object has its own natural frequency. Thus, the type of item placed on the scale also affects the vibration pattern. (iii) We empirically observed that the characteristics of the smartphone's vibration motor changes under different battery levels and literature suggests that the internal temperature also affects the motor's characteristics. To obtain a baseline vibration characteristic, we obtained the zero-load vibration signal every time before placing the object onto the phone. We extracted the object's load based on the difference between the zero-load and with-load vibration.

Overall, we present the design and implementation of VibroScale, a vibration-based weight-measurement scale using a smartphone. VibroScale can measure the weight of objects of the size of a tennis ball. We evaluated VibroScale on more than 50 fruits and other everyday objects. The results show that our method can indeed measure the weight of fruits with a mean absolute error of 12.4 grams for one type of object. We highlight one application case of fruit calorie estimation by combining VibroScale with an image based fruit recognition system. However, as an alternative of a scale, in more general cases, our technique can be used to measure any object of similar size with moderate mean absolute error of 33.0 grams.

2 RELATED WORK

Work closest to VibroScale falls under two categories: novel weight measurement methods, and use of vibration in various situations.

2.1 Novel Weighing Methods

Although weight is one of the most fundamental measurements, and weighing demand is arguably pervasive in daily life, however, little attention has been paid to novel weight measurement device and equipment. At a more broad weight measure level, including weight measurement of humans, livestock, or vehicles, there are a few studies that propose novel techniques for the corresponding weight measurement [1, 3, 5, 6]. Although the basic need to measure an object or a food item has existed for long (especially for people in diet), however, there is no effective weight measurement method available when a weighing scale is not present.

2.2 Vibration-based Sensing Technology

Vibration-based sensing has been employed in a broad range of devices and applications, including activity recognition [7, 19], speech recognition [14, 15], human computer interaction [12], smartphone environment recognition [2, 4], security and privacy [10, 16], as well as IoT application [20]. If we categorize the existing vibration-sensing works in terms of the source of the vibration, there are three types of applications: sensing intrinsic object vibration, sensing human physiological vibration, and sensing the vibration induced by an add-on vibration motor.

2.2.1 Intrinsic Object Vibration Sensing. In the field of activity recognition, many daily activities exhibit vibration at unique frequency bands, such as typing, drilling, and using coffee machine, which can be detected using either wearable sensors [7] or ambient sensing [13, 19]. Laput et al. [7] used a smartwatch to detect the vibration signatures of handheld objects or hand gestures and infer the ongoing activities. Zhang et al. [19] implemented a system that could scan the room environment and detect vibrating objects and perform the activity inference task. Marquardt et al. [13] presented that keystroke on a keyboard could be detected from a nearby smartphone, and the text entered using the nearby keyboard could be discovered using accelerometer signal and a malicious application. These works above detect the inherent object vibration to perform recognition tasks.

2.2.2 Human Physiological Vibration Sensing. Human body parts such as the heart and vocal chord exhibit specific vibration patterns. These vibrations can be collected to detect various events. For example, Michalevsky et al. demonstrated that speech recognition could be achieved using the gyroscope in smartphone located near the speaker [15]. Lin et al. [10] proposed a novel method of biometrics that could generate secret key based on heartbeat using piezoelectric sensor. Maruri et al. [14] realized robust speech recognition and human-to-human communication using a smart glass with a piezoelectric sensor located in the nasal pads.

2.2.3 Vibration Motor Induced Active Sensing. Even when the object of interest does not vibrate, vibration can be induced by adding a vibration motor on the object and detected by an IMU sensor for recognition and communication tasks. The sensing is conducted in an *active* manner in that it requires an external energy source input rather than the object to be sensed itself. Sen et al. [16] employed a vibration motor to share keys between smart devices. Zhao et al. [20] detected the fill-level of a waste bin using a motor and IMU attached on the bin, while Ma et al. [12] proposed a vibration-based communication method over human skin and showcased that between an on-wrist smartwatch and a hand-held smartphone. Besides designing a gadget with motor and IMU, the smartphone built-in motor and IMU are used for actively sensing the surface where the smartphone is placed on [2] and infer the smartphone position [4]. In this work, we propose a novel object measurement method using smartphone without any additional components, and validate the effectiveness and efficacy of our method as an alternative of weighing scale through various tests.

3 OVERVIEW OF VIBROSCALE

As mentioned previously, the overall goal of VibroScale is to objectively measure the weight of items. VibroScale attains this goal by using a novel vibration-based approach to measure the weight of any object that is placed on it. Overall, VibroScale consists of a smartphone with the VibroScale application running. This app controls the vibration motor and collects data from the accelerometer. VibroScale uses this data to calculate the placed item's weight.

3.1 Device and Implementation

For our experiments, we used a Google Nexus 5 smartphone running Android 4.4 (API level 19). This smartphone has InvenSense's

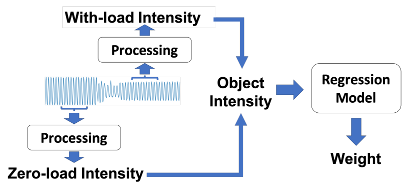

Figure 2: The data processing and modeling pipeline.

MPU-6515 accelerometer embedded into it. The vibration motor present in the used smartphone has a vibration frequency that varies between 25 Hz and 32 Hz.

To measure the weight of the object, VibroScale first turns on the smartphone's vibration motor and measures the vibration intensity for 3 seconds. During this phase, the VibroScale smartphone application displays '*WAIT*' on the smartphone, guiding the user not to place any object on it at that time. This step allows VibroScale to collect the baseline (or reference) weight at the specific battery level and internal temperature. Next, at the end of 3 seconds, the user is guided to place the object on the smartphone. The two-stage design stems from the following observation: the zero-load vibration (when no item is placed) amplitude varies based on battery levels. Moreover, the with-load vibration (when an item is placed) amplitude also varies even when testing the same object at different times. However, we observed that difference between with-load phase and zero-load phase has little variance for the same object.

The VibroScale app continuously measures and records the vibration amplitude by collecting data from its accelerometer. Data are collected from all three accelerometer axes. The accelerometer is sampled at 200 Hz which is substantially high to capture vibration generated by the motor, even at the highest frequency. We use an Ozeri ZK14-S kitchen and food scale to measure the weight of the objects.

3.2 Data Processing and Modeling

The first step in the data processing involves ensuring that the data collected from the accelerometer are at 200 Hz. In fact, due to hardware limitations, the data collected for a second are not 200 Hz, we interpolate the data using linear interpolation method. Next, we extract the zero-load stage (first 3 seconds) accelerometer's y-axis signal $\dot{a}_t$ (t = 0,..., T_1), and the with-load stage (after 3 seconds) accelerometer's y-axis signal $\tilde{a}_t$ (t=0,..., T_2). We use Equation 1 and Equation 2 to obtain the zero-load intensity and with-load intensity.

$$\dot{I} = \frac{1}{T_1}\sum_{t=0}^{T_1} ||\dot{a}_t - \frac{1}{T_1}\sum_{t=0}^{T_1}\dot{a}_t|| \tag{1}$$

$$\tilde{I} = \frac{1}{T_2}\sum_{t=0}^{T_2} ||\tilde{a}_t - \frac{1}{T_2}\sum_{t=0}^{T_2}\tilde{a}_t|| \tag{2}$$

Finally, we obtain the relative intensity induced by the object by computing the difference between $\dot{I}$ and $\tilde{I}$, as shown in Equation 3.

$$I = \dot{I} - \tilde{I} \tag{3}$$

Figure 2 pictorially presents the entire process. This relative induced intensity I is used to build a linear regression model, which we use to predict the weight of the object.

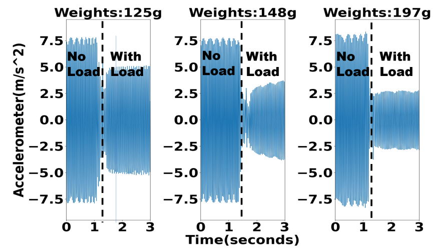

Figure 3: Variation in vibration for when no weight is placed on the smartphone or when various weighted apples are placed on the smartphone.

4 EXPERIMENTS AND RESULTS

Dataset: To determine the possibility of determining an object's weight using VibroScale, we used the following 52 distinct items: apples (24 pieces), onions (16 pieces), green pepper (6 pieces), and non-food tableware including glasses and bowls (6 pieces). The variation of weights for each of the categories in listed in Table 1.

Table 1: Objects used in the study along with their actual weight range and error in predicted weights.

	Apple	Onion	Pepper	Tableware	All
number	24	16	6	6	52
min/max (g)	114/202	53/376	118/164	59/263	53/376
MAE (g)	12.4	41.3	16.2	32.4	33.0
MAPE (%)	7.7	33.2	11.9	25.9	23.7

Evaluation strategy: To evaluate the performance of our model, we performed a leave-one-object-out cross validation. This allows us generalized model, which is item independent. After we built a model on each type of objects, a model was built on all 52 objects, being trained 51 items and tested with the 52^{nd} item. We have tried using different axes of accelerometer and PCA components of x, y-axis and x, y, z-axis for intensity calculation. The dominant frequency components of different axes were also tested to derive intensity. We observed that the most prominent variation was observed when using y-axis data in time domain. Figure 3 shows the variation in vibration for different objects.

Result: Figure 4 shows the distribution of relative vibration intensity based on weight. The relationship is obviously noisy due to the variation in natural frequency of the objects and due to the employed prediction model. Nonetheless, we observed a moderate linear correlation, with a Pearson correlation coefficient as 0.70 (p=6e-9). Overall, the objects used in our study ranged from 53 grams to 376 grams. When we performed a leave-one-object-out cross validation, we observed that the mean absolute error (MAE) in predicting the weight of the object was 33 grams, and the mean absolute percentage error (MAPE) was 23.7%. The MAE and MAPE for apples were only 12.4 grams and 7.7%, while they were 41.3 grams and 33.2% for onions. Table 1 presents the MAE and MAPE for the different objects.

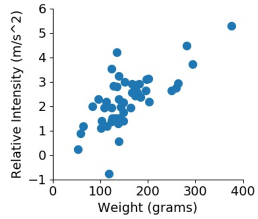

Figure 4: Distribution of the relative intensity for all objects.

Figure 5 shows the variation in actual and predicted weight of apples. In the evaluation of the weight prediction for the 24 apples, for apples weighing in range of 114 to 202 grams, we observed a MAE of 12.4 grams and a standard deviation of 10.7 grams, and a MAPE of 7.7%, showing promise in our proposed approach.

5 DISCUSSION AND FUTURE WORK

In this paper, we present the possibility of measuring the weight of objects using a smartphone. This has several implications:

Application: Objectively measuring weight of food objects has applications in diet monitoring [18]. It can be used for monitoring intake and measuring the calories consumed during transient eating episodes. It can also help in determining how much quantity of food item has been bought during a grocery shopping episode. Consider a scenario where a person captures image of the food being consumed and then places a food item on the smartphone running VibroScale. In such a scenario, an image recognition algorithm can recognize the food type, while the phone can measure the weight of the item. Combining the two outcomes can allow estimating the amount of calories present in the consumed food item.

Effect of various factors: Currently, we measured the weight of items when the phone is placed on the table. In future, we will investigate the effect of factors, including the surface (hand, wooden table, or steel table), contact area, natural frequency of the object, and even the phone battery on the performance of the system. In addition, the accuracy in different weight ranges will be studied. We also noticed that fruit items with thick peels (such as some special type of orange) might not work well using VibroScale, which makes sense since the thick peels have effect as a cushion layer between object and smartphone, affecting the vibration intensity in a complex way.

6 CONCLUSION

In this paper, we present the design and implementation of VibroScale, a smartphone-based system that can measure the weight of object placed on it. VibroScale utilizes the vibration intensity of the smartphone's vibration motor and its built-in accelerometer to predict the weight. Through a small study, we demonstrate that VibroScale can indeed compute the the weight of objects with a mean absolute error of 12.4 grams for a single type of objects.

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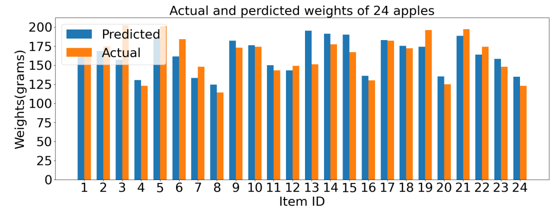

Figure 5: Predicted vs actual weights of apples in our study.

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