Poster: VibroScale: Turning Your Smartphone into a Weighing Scale

Shibo Zhang, Qiuyang Xu, Sougata Sen, Nabil Alshurafa
Northwestern University
Evanston, IL, United States

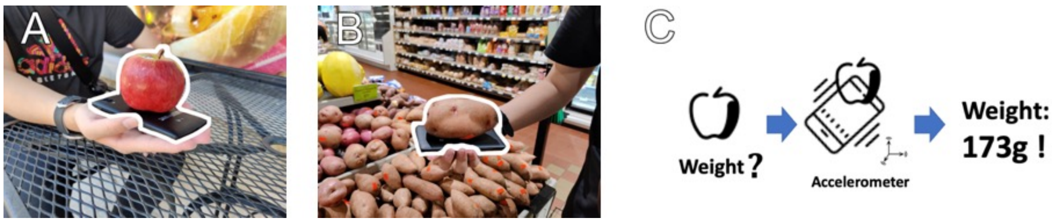

Figure 1: Use case of VibroScale weighing food items (A) in food courts and (B) in grocery stores. (C) System overview.

ABSTRACT

Smartphones, with their ubiquity and plethora of embedded sensors enable on-the-go measurement. Here, 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 the weight 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 scale, has several possible uses, particularly in weighing small food items. We designed a smartphone app and regression algorithm, which we termed VibroScale, that estimates the relative induced intensity of an object placed on the smartphone. We tested our proposed method using more than 50 fruits and other everyday objects of different sizes and weights. Our smartphone-based method can measure the weight of fruit without relying on an actual 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 the weight of various types of objects.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing systems and tools**; • **Applied computing → Engineering**.

KEYWORDS

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

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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 scale to measure weight). However, it would be 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 smartphone. Modern smartphones are equipped with several sensors that 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 use various smartphone components and sensors.

Among the various components and sensors in the smartphone, here we focus on using the accelerometer and the smartphone's vibration motor. We hypothesized that the vibration caused by a smartphone's vibration motor is different when a weight is placed on the smartphone, as compared with when no weight is placed on the smartphone. Here, we present VibroScale, a system that explores the change in vibration when a weight is placed on the smartphone (Figure 1). VibroScale controls the vibration of the smartphone's vibration motor and measures the amplitude of vibration using the smartphone's built-in accelerometer. Not only does a weight placed on top of the smartphone dampen the vibration (as captured by the accelerometer), but dampening is linearly correlated with 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) The characteristics of the smartphone's vibration motor change under different battery levels. Literature also suggests that the internal temperature affects the motor's characteristics. Thus it was necessary to obtain a baseline vibration characteristic.

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 the size of a tennis ball. We evaluated VibroScale using more than 50 fruits and other everyday objects. Our 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 system 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, little attention has been paid to novel weight measurement devices and equipment. At a more broad weight measure level, including weight measurement of humans, livestock, or vehicles, a few studies 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 individuals with specific diets), there is no effective weight measurement method available when a 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], and security and privacy [10, 16], as well as Internet of Things (IoT) applications [20]. If we categorize the existing vibration-sensing works in terms of the source of the vibration, there are three types of applications: (i) sensing intrinsic object vibration, (ii) sensing human physiological vibration, and (iii) 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 hand-held 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] showed that a 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 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 Inertial Measurement Unit (IMU) sensor for recognition and communication tasks. 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 on which the smartphone is placed [2] and infering the smartphone position [4]. In this work, we propose a novel object measurement method using a smartphone without any additional components, and we validate the effectiveness and efficacy of our method as an alternative to using a scale through various tests.

3 OVERVIEW OF VIBROSCALE

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. VibroScale is a smartphone app that controls a smartphone's 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 MPU-6515 accelerometer embedded into it. The vibration motor present in the smartphone has a vibration frequency that varies between 25 and 32 Hz.

To measure the weight of the object, it is necessary to first obtain the baseline vibration characteristic. Thus, VibroScale first turns on the smartphone's vibration motor and measures the vibration

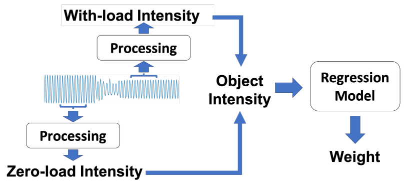

Figure 2: Data processing and modeling pipeline.

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 (zero-load vibration or reference) weight at the specific battery level and internal temperature. After the initial 3-second measurement, the user is guided to place the object on the smartphone. The two-stage design stems from the observation that the zero-load vibration amplitude (when no item is placed) varies based on battery levels. Moreover, the with-load vibration amplitude (when an item is placed) also varies even when testing the same object at different times. However, we observed that the 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 using all three accelerometer axes. The accelerometer is sampled at 200 Hz, which is sufficiently 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 actual weight of the objects.

3.2 Data Processing and Modeling

The first step in data processing involves ensuring that the data collected from the accelerometer are at 200 Hz. If, due to hardware limitations, the data collected for any second are not 200 Hz, we interpolate the data using a 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 Equations 1 and 2 to obtain the zero-load intensity and with-load intensity, respectively.

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

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

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.

4 EXPERIMENTS AND RESULTS

Dataset: To determine the possibility of determining an object's weight using VibroScale, we used the following 52 distinct items:

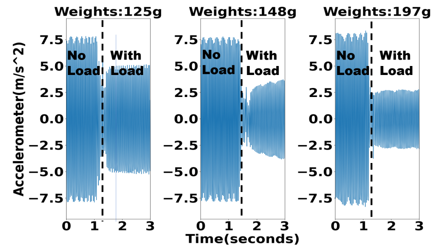

Figure 3: Variation in vibration when no weight is placed on the smartphone or when variously weighted apples are placed on the smartphone.

apples (24 pieces), onions (16 pieces), green pepper (6 pieces), and non-food tableware including glasses and bowls (6 pieces). The weights for each of the categories is listed in Table 1.

Table 1: Objects used in the study along with their actual weight range and error in predicted weights. MAE, mean absolute error; MAPE, mean absolute percentage error.

	Apple	Onion	Pepper	Tableware	All
Number (N)	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 for each object and then for all objects combined. When evaluating the N items, we build a linear regression model using N-1 items, and test it on the Nth item, we repeat this step N times. We tested different axes of the accelerometer and performed Principle Component Analysis (PCA) to calculate the PCA components of the x/y axis and x/y/z axis for intensity calculation. The dominant frequency components of the different axes were also tested to derive intensity. In the end, we found that the most prominent variation was observed when using y-axis data in the 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 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 of 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 12.4 grams and 7.7%, respectively, while they were 41.3 grams and 33.2% for onions. Table 1 presents the MAE and MAPE for the different objects.

Figure 5 shows the variation in actual and predicted weight of apples. For apples weighing between 114 and 202 grams, we

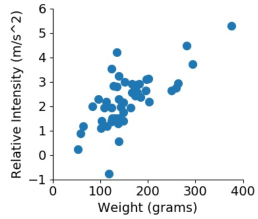

Figure 4: Distribution of the relative intensity for all objects.

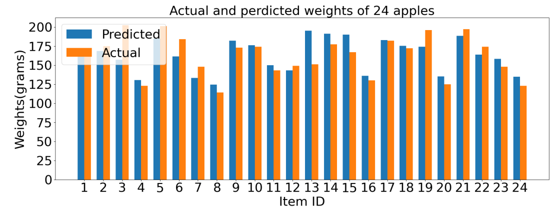

Figure 5: Predicted vs actual weights of apples in our study.

observed a MAE of 12.4 grams with a standard deviation of 10.7 grams and a MAPE of 7.7%.

5 DISCUSSION AND FUTURE WORK

We presented 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 calories consumed during transient eating episodes. It can also help in determining how much food has been purchased during a grocery shopping episode. Using a scenario in which a person captures an image of the food being consumed and then places the food item on the smartphone running VibroScale an image recognition algorithm can recognize the food type while the phone measures the weight of the item. Combining the two outcomes can allow estimating the amount of calories present in the food item.

Influencing factors: Currently, we measured the weight of items when the phone is placed on the table. In the future, we will investigate the effect of varying factors, including the surface on which the smartphone is placed (e.g., a hand, wooden table, or steel table), contact area between the object and smartphone, natural vibrating frequency of the object, and even the phone battery state (which can effect the vibration motor) on the performance of the system. In addition, the accuracy in different weight ranges beyond 376 grams 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

Here, we present the design and implementation of VibroScale, a smartphone-based system that can measure the weight of an object placed on it. VibroScale uses the vibration intensity of the smartphone's vibration motor and its built-in accelerometer to predict the object's weight. In this study, we demonstrate that VibroScale is able to compute the weight of individual objects with reasonably high accuracy.

REFERENCES

[1] Elder Akpa Akpro Hippocrate, Hirohiko Suwa, Yutaka Arakawa, and Keiichi Yasumoto. 2016. Food Weight Estimation using Smartphone and Cutlery. In *Proceedings of the First Workshop on IoT-Enabled Healthcare and Wellness Technologies and Systems (IoT of Health '16)*.

[2] Jungchan Cho, Inhwan Hwang, and Songhwai Oh. 2012. Vibration-Based Surface Recognition for Smartphones. In *International Conference on Embedded and Real-Time Computing Systems and Applications (RTCSA'12)*.

[3] Dragan Cveticanin. 2003. New Approach to the Dynamic Weighing of Livestock. *Biosystems Engineering* 86, 2 (2003), 247 – 252.

[4] Irina Diaconita, Andreas Reinhardt, Delphine Christin, and Christoph Rensing. 2015. Inferring Smartphone Positions Based on Collecting the Environment's Response to Vibration Motor Actuation. In *Symposium on QoS and Security for Wireless and Mobile Networks (Q2SWinet '15)*.

[5] Theophilus Ewetumo, Kayode D Adedayo, Yusuf B Lawal, Abiodun T Edun, and Joseph E Orokhe. 2019. Development of an Automatic Body Mass Index Measurement Machine. *FUOYE Journal of Engineering and Technology* 4, 2 (2019).

[6] Sivaramalingam Kirushnath and Boniface Kabaso. 2018. Weigh-in-motion Using Machine Learning and Telematics. In *2018 2nd International Conference on Telematics and Future Generation Networks (TAFGEN)*. 115–120.

[7] Gierad Laput, Robert Xiao, and Chris Harrison. 2016. Viband: High-Fidelity Bioacoustic Sensing Using Commodity Smartwatch Accelerometers. In *Proceedings of the 29th Annual Symposium on User Interface Software and Technology*. 321–333.

[8] Neal Lathia, Gillian M Sandstrom, Cecilia Mascolo, and Peter J Rentfrow. 2017. Happier People Live More Active Lives: Using Smartphones to Link Happiness and Physical Activity. *PloS one* 12, 1 (2017), e0160589.

[9] Robert LiKamWa, Yunxin Liu, Nicholas D Lane, and Lin Zhong. 2013. MoodScope: Building a Mood Sensor from Smartphone Usage Patterns. In *International conference on Mobile systems, applications, and services*. 389–402.

[10] Qi Lin, Weitao Xu, Jun Liu, Abdelwahed Khamis, Wen Hu, Mahbub Hassan, and Aruna Seneviratne. 2019. H2B: Heartbeat-based Secret Key Generation Using Piezo Vibration Sensors. *Proceedings of the 18th International Conference on Information Processing in Sensor Networks* (2019).

[11] Guangwen Liu, Masayuki Iwai, Yoshito Tobe, Dunstan Matekenya, Khan Muhammad Asif Hossain, Masaki Ito, and Kaoru Sezaki. 2014. Beyond Horizontal Location Context: Measuring Elevation Using Smartphone's Barometer. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct Publication* (Seattle, Washington) *(UbiComp '14 Adjunct)*. Association for Computing Machinery, New York, NY, USA, 459–468.

[12] Dong Ma, Yuezhong Wu, Ming Ding, Mahbub Hassan, and Wen Hu. 2020. Skin-MIMO: Vibration-based MIMO Communication over Human Skin. arXiv:2001.11574 [cs.NI]

[13] Philip Marquardt, Arunabh Verma, Henry Carter, and Patrick Traynor. 2011. (sp)iPhone: Decoding Vibrations From Nearby Keyboards Using Mobile Phone Accelerometers. In *ACM Conference on Computer and Communications Security (CCS '11)*. 551–562.

[14] Héctor A. Cordourier Maruri, Paulo Lopez-Meyer, Jonathan Huang, Willem Marco Beltman, Lama Nachman, and Hong Lu. 2018. V-Speech: Noise-Robust Speech Capturing Glasses Using Vibration Sensors. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 2, 4, Article 180 (2018), 23 pages.

[15] Yan Michalevsky, Dan Boneh, and Gabi Nakibly. 2014. Gyrophone: Recognizing Speech from Gyroscope Signals. In *23rd USENIX Security Symposium (USENIX Security 14)*. USENIX Association, San Diego, CA, 1053–1067. https://www.usenix.org/conference/usenixsecurity14/technical-sessions/presentation/michalevsky

[16] Sougata Sen and David Kotz. 2020. VibeRing: Using Vibrations from a Smart Ring as an Out-of-band Channel for Sharing Secret Keys. In *International Conference on the Internet of Things (IoT'20)*.

[17] Shichao Yue and Dina Katabi. 2019. Liquid Testing with Your Smartphone. In *International Conference on Mobile Systems, Applications, and Services*. 275–286.

[18] Shibo Zhang, Dzung Tri Nguyen, Gan Zhang, Runsheng Xu, Nikolaos Maglaveras, and Nabil Alshurafa. 2018. Estimating Caloric Intake in Bedridden Hospital Patients with Audio and Neck-Worn Sensors. In *Proceedings of the 2018 IEEE/ACM International Conference on Connected Health: Applications, Systems and Engineering Technologies* (Washington, DC) *(CHASE '18)*. Association for Computing Machinery, New York, NY, USA, 1–2.

[19] Yang Zhang, Gierad Laput, and Chris Harrison. 2018. Vibrosight: Long-Range Vibrometry for Smart Environment Sensing. In *Annual ACM Symposium on User Interface Software and Technology* (Berlin, Germany) *(UIST '18)*. 225–236.

[20] Yiran Zhao, Shuochao Yao, Shen Li, Shaohan Hu, Huajie Shao, and Tarek F. Abdelzaher. 2017. VibeBin: A Vibration-Based Waste Bin Level Detection System. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 1, 3, Article 122 (2017), 22 pages.