REACH: Enabling Single-Handed Operation on Large Screen Mobile Devices

Varun Perumal
Dept. of Computer Science
University of Toronto
varun@cs.toronto.edu

Ahmadul Hassan
Elec. & Computer Eng.
University of Toronto
ahmadul.hassan@gmail.com

Zahid Abul-Basher
Mech. & Industrial Eng.
University of Toronto
zahid@cs.toronto.edu

ABSTRACT

Categories and Subject Descriptors

H.5.2 [**Information interfaces and presentation**]: User Interfaces—graphical user interfaces

General Terms

Design, Experimentation, Human Factors

Keywords

Data analytics

1. INTRODUCTION

2. RELATED WORK

Many researchers have suggested that the devices should be intelligent enough to detect user's situation for better support as in [9] and [13]. For instance, *ability based design* aims to find the best match between the ability of the users and the interfaces [19]. There are also researches to recognize the activity of users on devices (also known as *activity recognition*). Choudhuri *et al.* [2] built a wearable device with sensors to detect the activity of the users. In [16], Laerhoven used an accelerometer in a phone to recognize different motions of walking, climbing stairs, *etc.* Schmidt *et al.* [13] also used accelerometer but to detect both the user movement and the place of the device itself whether it is in the hand or on a table or in a suitcase. GripSense [4] used gyroscope and vibration motor to classify the user's touches based on the pressure on the screen. There is also many studies in the context of detecting hand postures. Harrison *et al.* [6] and Kim *et al.* [12] used touch sensors to detect the pattern of user's grips on mobiles. Furthermore, Taylor and Bove [15] used accelerometers to improve the detection of the changes in the grip dynamically.

Many researchers also studied hand posture on devices to make them more intelligent and interactive to the situations caused by posture. For instance, Wobbrock *et al.* [20] studied different hand postures and measured the finger performance with mobile devices. Holz *et al.* [8] have evaluated systematic error in selecting the target with finger touch. Researchers [7, 17, 11] also found that mobile interfaces are designed for double-handed operation although users may prefer to use one single hand. Karlson *et al.* [10] studied those interfaces and evaluated the performance of thumb mobility on those interfaces. Azenkot and Zhai [1] showed that different hand postures lead to different touch patterns, thus, effect the performance of typing on mobile devices. AppLens and LaunchTiles [11] designed interfaces based on different thumb gestures for one handed interactions.

Fitzmaurice *et al.* [3] introduced the idea of "graspable user interfaces" where you can control the interface by interacting with a physical object. SqueezeBlock [5] is an implementation of this idea in which it provides haptic feedback according to the level of "squashiness" on a physical object. Wimmer *et al.* [18] deployed optical fibers into a surface of device to detect grasping pressure. Harrison *et al.* [6] used FSRs for squeezing pressure detection. Strachan and Murray-Smith [14], used muscle tremor as a form of input to detect pressure on devices by leveraging accelerometer logs.

3. OVERALL DESIGN OF REACH

The design of REACH involves three distinct phases - building the hardware to collect and transmit force sensor data, performing offline analysis to train a classification model and finally performing real-time evaluations to detect grip patterns and perform a corresponding action.

4. HARDWARE DESIGN OF REACH

5. SOFTWARE DESIGN OF REACH

In addition to the hardware implementation by selecting appropriate force sensors and locating them in the appropriate places around the mobile device, we also build the classifier for the hand grip. In this section, we discuss how we collect force sensor values from mobile device for training and how we implement the classifier for grip pattern detection. We then used the model to predict the pattern in realtime manner.

For training the model, we used the Weka (Witten & Frank 2005) machine learning library for Java. We used Bayesian network, Naive Bayes and Support vector machine machine algorithms for training the model on the collected data. We performed off-line training on a laptop and extracted the parameters of the best model to implement the realtime version of REACH.

5.1 Tap Detection as Proxy

While waiting for the hardware to be completed, we decided to perform some experiments to provide insight into how to classify the grip patterns. Tap detection was chosen as a proxy for grip pattern detection. We used the accelerometer data available from an Android phone to try and classify instances when a user performs a single tap on the back of the device.

The accelerometer data from 3 axis (x, y, z) is analogous to the force data available from the 16 sensors for grip detection. Similarly, both accelerometer and force data will change when an action is performed by the user. The only difference is that the accelerometer data changes depending on the orientation of the phone, while the force data is unaffected. To mitigate this, all data collected and analyzed for tap detection focused on keeping the phone in portrait orientation, the y-axis facing away from the floor and the z-axis facing towards the user.

5.1.1 Determine Window Size

The Android sensor collects accelerometer data on a periodic basis. This sampling interval is neither guaranteed nor specified by the Android SDK, but using the default mode, it was found to be 20ms on *average*. After analyzing the data, it was noticed that the characteristic pattern of a single tap lasted for a duration of 400ms on average. This duration is defined as the *window duration*.

Dividing the window duration by the sampling interval gives us a *window size* of 20. The accelerometer data is partitioned into windows with the specifications above, and implemented as a *sliding window*. This means that the starting time for each subsequent window differs by the sampling interval. Contrast this against a *jumping window*, where the start time for subsequent windows would be the window duration. Using the *sliding window* protocol ensures that a possible tap is not missed during the evaluation process.

Picking the right window size is crucial since it has a direct impact on the accuracy of the classification model. If the *window size* is too small, then the complete characteristic pattern of a tap will not be captured, leading to incorrect classifications. However, using a window size that is too large will capture extraneous noisy data that will also reduce the classification accuracy. This topic will again be explored for grip pattern detection.

5.1.2 Determine Features

Upon observing the data, it was noticed that acceleration values of the x, y and z axis all changed when the tap action was performed. The *inter*-window change was captured by calculating the *mean* for a window, and this was used as one of the features for training the model. There was a visible change in the acceleration values within the window duration, and this *intra*-window change was represented by calculating the *variance* of a window.

5.1.3 Classify a Tap

Even though a windowing principle was used, windows clustered near a tap duration all show a similar characteristic pattern, albeit time-shifted. Therefore while performing the manual classification of the training data, we decided to label, on average, 20 windows as a single tap. This means that when a tap is being evaluated with real-time data, we would expect 20 back-to-back windows all to be predicted as a tap. Once such a scenario is detected, we would report a successful tap as being detected.

5.1.4 Tap Model Performance

5.2 Grip Classifier

We used the insights gained from tap detection to guide our grip classification process. We begin by attempting to classify three grip patterns in our prototype: None, Squeeze, and Reach. In None, the subject holds the device without performing any activity. In Squeeze, the subject is applying a squeeze-force on the device and in Reach, the subject is moving his thumb finger to reach the top of the device while holding the device.

The 12 force sensors around the device continuously reported data every 1 ms on average. Based on our experience with tap detection, we felt that these values could be safely aggregated into a 20ms sampling interval for the purpose of grip detection. The figure below shows the change in a sensors value for a *window size* of 60. We can clearly see that choosing a value of 20 would result in the loss of valuable information, while a value of 60 would admit noisy data. It was determined that a *window size* of 50 represents the average case.

The logged information was then calculated and we calculated three metrics; mean, variance, and delta variance as features to train a classifier model. Therefore, the training data from each grip consists from **** numerical values and the final data consists from **** numerical values for each grip pattern.

5.2.1 Variability of Training Data

After we identified the grip pattern classes, we collected the training data from 1 subject. The individual was asked to perform Hold, Squeeze, and Reach every 15 seconds for a duration of 1 minute. This process was repeated 3 times.

6. EVALUATION

6.1 Off-line Evaluation

6.2 Realtime Evaluation

7. CONCLUSIONS AND FUTURE WORKS

8. REFERENCES

[1] S. Azenkot and S. Zhai. Touch behavior with different postures on soft smartphone keyboards. In *Proceedings of the 14th International Conference on Human-computer Interaction with Mobile Devices and Services*, MobileHCI '12, pages 251–260, 2012.

[2] T. Choudhury, S. Consolvo, B. Harrison, J. Hightower, A. LaMarca, L. LeGrand, A. Rahimi, A. Rea, G. Bordello, B. Hemingway, et al. The mobile sensing platform: An embedded activity recognition system. *Pervasive Computing, IEEE*, 7(2):32–41, 2008.

[3] G. W. Fitzmaurice, H. Ishii, and W. A. S. Buxton. Bricks: Laying the foundations for graspable user interfaces. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '95, pages 442–449, 1995.

[4] M. Goel, J. Wobbrock, and S. Patel. Gripsense: using built-in sensors to detect hand posture and pressure on commodity mobile phones. In *Proceedings of the 25th annual ACM symposium on User interface software and technology*, pages 545–554. ACM, 2012.

[5] S. Gupta, T. Campbell, J. R. Hightower, and S. N. Patel. Squeezeblock: Using virtual springs in mobile devices for eyes-free interaction. In *Proceedings of the 23Nd Annual ACM Symposium on User Interface Software and Technology*, UIST '10, pages 101–104, 2010.

[6] B. L. Harrison, K. P. Fishkin, A. Gujar, C. Mochon, and R. Want. Squeeze me, hold me, tilt me! an exploration of manipulative user interfaces. In *Proceedings of the SIGCHI conference on Human factors in computing systems*, pages 17–24, 1998.

[7] K. Hinckley and H. Song. Sensor synaesthesia: Touch in motion, and motion in touch. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '11, pages 801–810, 2011.

[8] C. Holz and P. Baudisch. Understanding touch. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '11, pages 2501–2510, 2011.

[9] P. Johnson. Usability and mobility; interactions on the move. In *First Workshop on Human Computer Interaction with Mobile Devices*, 1998.

[10] A. K. Karlson and B. B. Bederson. Understanding single-handed mobile device interaction. Technical report, 2006.

[11] A. K. Karlson, B. B. Bederson, and J. SanGiovanni. Applens and launchtile: Two designs for one-handed thumb use on small devices. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '05, pages 201–210, 2005.

[12] K.-E. Kim, W. Chang, S.-J. Cho, J. Shim, H. Lee, J. Park, Y. Lee, and S. Kim. Hand grip pattern recognition for mobile user interfaces. In *Proceedings of the National Conference on Artificial Intelligence*, volume 21, page 1789, 2006.

[13] A. Schmidt, K. A. Aidoo, A. Takaluoma, U. Tuomela, K. V. Laerhoven, and W. V. d. Velde. Advanced interaction in context. In *Proceedings of the 1st International Symposium on Handheld and Ubiquitous Computing*, HUC '99, pages 89–101, 1999.

[14] S. Strachan and R. Murray-Smith. Muscle tremor as an input mechanism. 2004.

[15] B. T. Taylor and V. M. Bove Jr. Graspables: grasp-recognition as a user interface. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 917–926. ACM, 2009.

[16] K. Van Laerhoven and O. Cakmakci. What shall we teach our pants? In *Wearable Computers, The Fourth International Symposium on*, pages 77–83. IEEE, 2000.

[17] L. Weberg, T. Brange, and A. W. Hansson. A piece of butter on the pda display. In *CHI '01 Extended Abstracts on Human Factors in Computing Systems*, CHI EA '01, pages 435–436, 2001.

[18] R. Wimmer. Flyeye: Grasp-sensitive surfaces using optical fiber. In *Proceedings of the Fourth International Conference on Tangible, Embedded, and Embodied Interaction*, TEI '10, pages 245–248, 2010.

[19] J. O. Wobbrock, S. K. Kane, K. Z. Gajos, S. Harada, and J. Froehlich. Ability-based design: Concept, principles and examples. *ACM Transactions on Accessible Computing (TACCESS)*, 3(3):9, 2011.

[20] J. O. Wobbrock, B. A. Myers, and H. H. Aung. The performance of hand postures in front- and back-of-device interaction for mobile computing. *Int. J. Hum.-Comput. Stud.*, 66(12):857–875, 2008.