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

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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

5.2 Grip Classifier

We selected three grip pattern classes 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. 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.

The 12 force sensors around the device continuously reported data every 1 ms on average. 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.

6. EVALUATION

6.1 Off-line Evaluation

6.2 Realtime Evaluation

7. CONCLUSIONS AND FUTURE WORKS

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