Active Edge: Designing Squeeze Gestures for the Google Pixel 2

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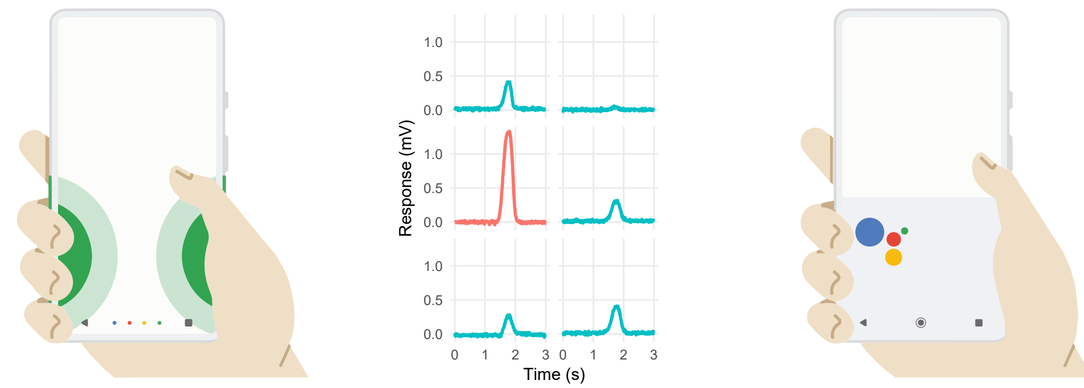

Figure 1: An overview of Active Edge interaction: A user squeezing the sides of their device (left), the raw signals observed on the sensors embedded in the device's chassis (middle), and the activated functionality – the Google Assistant (right).

ABSTRACT

Active Edge is a feature of Google Pixel 2 smartphone devices that creates a force-sensitive interaction surface along their sides, allowing users to perform gestures by holding and squeezing their device. Supported by strain gauge elements adhered to the inner sidewalls of the device chassis, these gestures can be more natural and ergonomic than on-screen (touch) counterparts. Developing these interactions is an integration of several components: (1) an insight and understanding of the user experiences that benefit from squeeze gestures; (2) hardware with the sensitivity and reliability to sense a user's squeeze in any operating environment; (3) a gesture design that discriminates intentional squeezes from innocuous handling; and (4) an interaction design to promote a discoverable and satisfying user experience. This paper describes the design and evaluation of Active Edge in these areas as part of the product's development and engineering.

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CCS CONCEPTS

• **Human-centered computing** → **Gestural input**; *Ubiquitous and mobile computing systems and tools*; • **Hardware** → **Sensor applications and deployments**.

KEYWORDS

Mobile gestures; grasp sensing; squeeze interaction.

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1 INTRODUCTION

The primary interaction surface for mobile devices is their touch-sensitive display – with a few physical buttons scattered around their periphery (e.g. power and volume control). With few exceptions, the back and sides of a device are inert surfaces that a user cradles with their hand to support it during touchscreen interaction. However, a user's grasp on a device can provide strong contextual cues about how they are interacting with it [8], and their grasp can change with the affordances that a device offers [30, 44]. These changes and cues can be developed into interactive gestures by designing a class of *intentional grasps* that a user can perform to invoke device actions. These stimuli motivated the development of *Active Edge*, a realisation of interactive grasp gestures featured on the Google Pixel 2 smartphone devices.

In comparison with touchscreen interactions, grasp gestures potentially enable faster and more ergonomic methods of device interaction. In many cases, users would not need to reposition their hands to perform grasp gestures and would be able to retain more secure one-handed control of the device. Moving interaction onto the back or sides of a device also reduces the clutter and obstruction of on-screen interaction from visual elements or the user's own hand.

However, interactive gestures on the back or sides of a device must be designed to be distinct enough to avoid confusion with incidental handling (e.g. picking up a device should not be confused with squeezing it). That is, designers must be careful in carving out a space for gestures that does not conflict with the device's other functions and can be integrated into a user's existing behaviour.

Feedback also plays a crucial role in creating the sensation of an interactive surface. When a user squeezes a device, it should *feel* as though the device's chassis has compliant qualities that reflect the gesture. This reinforces the interaction and promotes discovery by providing a mechanism for users to regulate their grasp and learn the gesture's parameters.

There has been substantial research on the design space for interaction on the back or sides of mobile devices (reviewed in the following section), but with limited maturation. Prior work has focused on hardware sensing techniques for prototyping interactions, but separate from that on the kinesic content and human factors of a user's grasp. Furthermore, there has been limited attention on how to design feedback that aids discovery, education, and use of an input space that lacks an output channel.

This paper describes the design, development, and evaluation of *Active Edge* across four core areas: (1) a qualitative study of the experiences for grasp-based interaction that benefit users; (2) the consistent and reliable hardware that is sensitive to minute forces on the sides of a rigid device chassis; (3) a gesture design and detection algorithm that reliably discriminates between intentional user grasps and incidental handling of the device; and (4) the interaction design that promotes discoverability and learnability.

2 BACKGROUND

Fitzmaurice [9, 10] introduced the concept of *Graspable User Interfaces*, where a user's grasp on a physical device manipulates some virtual function. Originally envisioned for stand-alone tools, Harrison et al. [16] integrated physical manipulators into the chassis of a handheld tablet device and explored mapping them to virtual controls – in particular, pinching on the side to control a scroll bar, or squeezing to isolate an item in a scrolling list.

Wimmer [66] developed a framework for exploring how a user's grasp on an object conveys meaningful contextual information through five factors: (1) the user's goal, (2) their relationship with the object, (3) their anatomy, (4) the properties of the object, and (5) the surrounding environment. He classified types of grasp and mechanisms for interpreting them – in particular, distinguishing between grasps that invoke a *primary* task or are *supportive* of another task (e.g. picking up a phone to answer a call vs. holding a phone while typing on a touchscreen keyboard), and are either *implicit* or *explicit* interactions (e.g. holding a phone to support it vs. holding a phone horizontally as a camera).

Recent work has also characterised the natural hand postures people use when interacting with mobile devices (without explicit graspable interaction) [8, 32].

Human Factors

People control their grasp on an object through a combination of feedback and feedforward control policies [39]. Motor control and learning are dependent on tactile feedback from an object and are informed by its invariant properties (e.g. its weight, surface friction, and shape) [15, 26]. To control grasp precisely, people are dependent on a combination of visual and tactile feedback [21, 29, 31, 52, 56] – with the loss of either causing an increase in control error. Visual feedback reduces absolute error more than tactile feedback, but reactions are faster to tactile feedback [27, 28].

Anthropomorphic measures of human grasp ability are also widely available [11, 45, 46]. This literature examines a population's maximum grip strength (rather than a 'comfortable' or 'relaxed' strength), but the results highlight the natural variance and covariates that should be expected from users when deploying grasp-based interactions. In particular, grip strength peaks at around 25 years of age, with female grip strength on average half that of male grip strength [11, 41]. There is also a significant difference in the grip strength between dominant and non-dominant hands [23], and a concave relationship with grip span [46, 51].

Sensing Technology

Force Sensing Resistors (FSRs) and strain gauges provide a simple and cost-effective method for adding force-sensing capabilities to an object [68, and Section 4]. Such sensors are unobtrusive and can be attached to an existing object without substantial engineering cost [e.g. 19, 20, 54, 63].

Capacitive sensors have also been extended to the sides and back of a device to detect a user's grasp, as they do for fingers on a touchscreen [e.g. 4–6, 17, 32, 35, 67]. However, capacitive sensors generally only sense contact and not force [cf. 53], and require a proximal electrical connection with a user's hand (i.e. their sensitivity is impeded by any insulating material). As a result, they are best suited for passive grasp-sensing interactions (reviewed below).

Some aspects of a user's grasp can be sensed using the existing sensors on mobile devices. For example, the accelerometer can detect a user's muscle tremor when they squeeze a device [58], or discrete tapping patterns on the sides or back of a device [14, 42]. The contact from a user's hand also creates a dampening effect on vibrations transmitted through a device chassis: if a known pattern is created – from a haptic actuator [13, 22] or an audio speaker [47, 62] – changes in the pattern on a corresponding receiver can be used to detect contact and pressure from a user's grasp.

Other techniques include measuring the skin's electrical impedance [40] or using optical sensors to sense the proximity and contact of a user's hand [38, 65].

Grasp Detection & Grasp Gestures

The design space for interaction using a user's grasp is broadly divided into two treatments: (1) active *grasp gestures* that a user performs to trigger an action, and (2) passive *grasp detection* that adapts an interface with contextual information from how a user is holding a device.

Holman et al. [20] and Tsukamoto et al. [61] explored one-handed navigation gestures created by a user squeezing their fingers around discrete regions of a device's edge – for example, squeezing one region to zoom into a map, and squeezing another to zoom out. Spelmezan et al. [54] and Wilson et al. [63] expanded these gestures using the level of force as a parameter to the action (e.g. the level/rate of zoom). Iso et al. [24] and Murao et al. [43] used a user's grasp as a biometric signal for authentication, while Hoggan et al. [19] used it as a personal communication medium between users. However, many of these projects focus on the use cases for grasp interactions, and discussion on issues of gesture design and its human factors is cursory.

Others have demonstrated the use of passive grasp detection to adapt interface elements to a user's posture. For example, it is known that touch accuracy on a mobile keyboard varies with the user's posture [1], and that posture information can be used to improve the spatial model for text entry decoding [12, 69]. Several of the sensing technologies described above were validated on their ability to discern several styles of grasp, with the intention of using this information for interface adaptation [18, 47, 67]. For example, Cheng et al. [5, 6] used capacitive sensors on the back of a device to characterise several grip/grasp postures for automatic keyboard adaptation and screen rotation.

Feedback and Control

In the above interaction research, feedback to the user is usually discussed as a collateral component: users receive discrete visual feedback of their actions as a result of their grasp, rather than as a mechanism to drive the control of their grasp. However, research on other types of force-based input has highlighted the necessity of continuous feedback for high-resolution, stable control [49, 64].

For graspable interaction, a natural feedback channel is the tactile sensation of the object being grasped [e.g. 25, 50]. On mobile devices, tactile feedback is usually supplied through a haptic actuator that can produce pulsed vibrational forces [2, 34, 48]. Although this type of actuator cannot produce effects that simulate the sensations of a soft or malleable material [55], it can simulate sensations of discrete impacts (e.g. a button or switch [3]).

3 SQUEEZABLE USER EXPERIENCES

The sides of a device are fertile surfaces for exploring new interactive experiences, but it is not obvious which experiences will be beneficial to users or whether grasp-based gestures will be ergonomic and natural for users to execute. Therefore, in order to explore the subjective qualities and user experience of grasp-based interaction we conducted a qualitative usability study using a low-fidelity prototype of a squeezable mobile device. The study sought answers to the following questions:

(1) Is the concept of grasping a device for interaction feasible and usable given that mobile devices are handheld and frequently handled without the intention to trigger any interaction?
(2) What are the use cases where grasp-based interaction is compelling to users?

Figure 2: The prototype device: FSRs embedded into a silicone case with an Arduino Pro Micro.

(3) How do grasp-based gestures compare with existing triggers for these interactions?

Although there are many different types of gesture that could be supported in this space (holding, sliding, swiping, squeezing, etc.), we decided to focus on a single gesture – a *squeeze* – as the principal mechanism for interaction. This is a narrow use of the space, but it allowed us to rigorously focus on a cohesive user experience around a unitary gesture.

Apparatus

We built a prototype device with FSRs (Velostat) adhered to the inner walls of a phone case (the lower half of both sides) and connected to an Arduino Pro Micro on the back (Figure 2). The Arduino measured the change in resistance of the material and communicated it over USB to an application running on a Google Pixel phone. The application implemented a simple algorithm that triggered a haptic vibration and a selected function (detailed below) whenever the measured force exceeded a certain threshold.

A pilot study was used to tune the force threshold to a comfortable level for each task.

Tasks & Design

We focused on four experiences that may benefit from grasp-based interaction and aligned with the affordance of a squeeze: (1) activating a voice assistant, (2) triggering a camera shutter, (3) silencing an alarm, and (4) a 'walkie-talkie' mode for voice-assistant interaction.

With each experience participants performed a set of tasks that involved either using an existing baseline trigger or a squeeze gesture (counterbalanced; detailed below with the results). After several repeated sets participants were asked for their preferred method on a seven-point scale and for their comments on the interaction. We also asked participants to perform actions that may cause false-triggering of the squeeze gesture (e.g. raising the phone to their ear, double-twisting the phone to switch between front and rear cameras, passing the phone between their hands).

Participants. Nine volunteers (five female; four male) participated in the study. They had a mean hand size of 72 mm (63–75 mm female; 71–82 mm male). Two participants were Apple iPhone users, and the remainder used Android-based devices. Participation lasted approximately 45 min.

Procedure & Results

Voice Assistant. Participants were asked to make a set of eight queries using the Google Assistant (e.g. 'turn on Bluetooth', 'what time is it in Germany?', 'what is the weather in Rio?'). Participants either squeezed the phone to trigger the assistant before each query, or used a voice trigger as a baseline ('Ok Google'; trained for each participant before the session to ensure reliability). Some of the queries were conversational: a subsequent query semantically followed the question and answer of the previous query.

Both methods performed reliably: there was only one failed squeeze gesture and two failed voice triggers, with no false-positive triggers. Overall, there was a strong preference for using the squeeze gesture (mean 6; Figure 3), but with comments cautioning that the squeeze gesture is not as universally accessible as a voice trigger (e.g. while driving or cooking). Other comments highlighted that it felt 'natural to be able to squeeze and speak', and lamented the repetitious nature of the voice trigger.

Silence Alarm. Participants were asked to place the phone on a desk and face away from it. After a moment, an alarm would sound and they were to silence it. Participants squeezed the phone to silence the alarm, and compared it to the corresponding method on their primary device (either an on-screen or hardware button).

Over half of the participants (5) failed at least one attempt to silence the alarm using the squeeze gesture, but preference

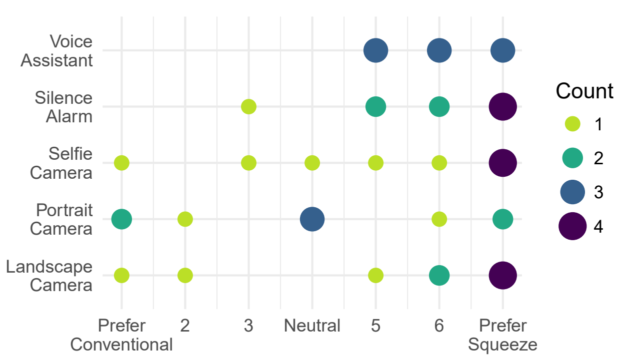


Figure 3: Participants' preferences between conventional methods and squeezing.

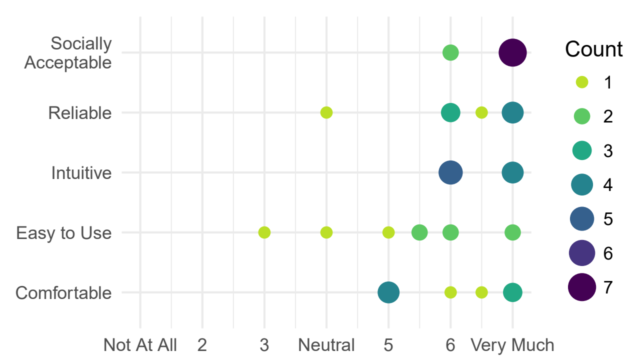


Figure 4: Participants' overall satisfaction with squeeze gestures along several dimensions.

scores for it were still high (mean 5.9; Figure 3). Comments focused on the ease of the squeeze gesture ('less fumbling').

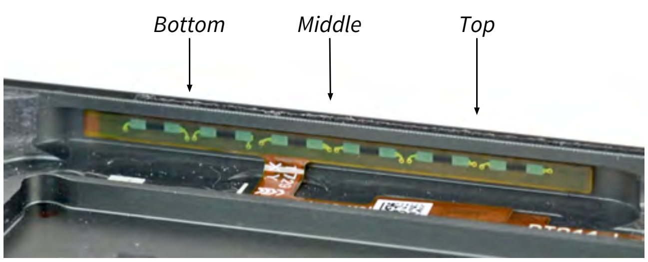
Camera Shutter. Participants were asked to take photos in landscape, portrait, and selfie (i.e. front camera) orientations using either a squeeze gesture or an on-screen shutter button.

Only two participants had any instances of a missed shutter using the squeeze gesture, but preferences were mixed. In landscape and selfie orientations, the squeeze gesture was preferred (means of 5.3 and 5.2; Figure 3), but responses were neutral in the portrait orientation (mean 4). Comments cited ergonomic issues from wrapping a hand around the back of a device at arms-length. Other comments focused on concerns about hand tremor from the squeeze gesture distorting the image (although this was not observed in practice).

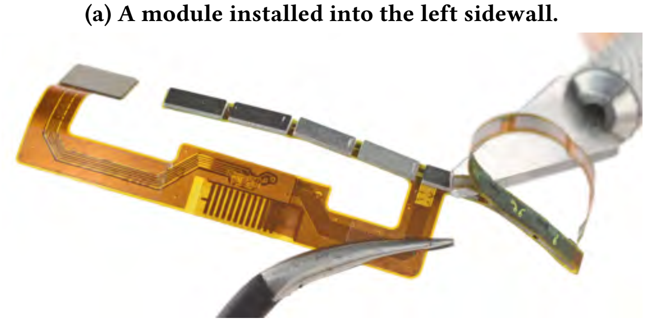
Walkie-Talkie. We also implemented a 'walkie-talkie' mode for the voice assistant to examine prolonged gestures: participants would squeeze and hold as they spoke their query – releasing to commit it. As this is a novel use specific to the squeeze gesture, there was no baseline for comparison and only comments were collected.

Participants liked the idea conceptually, but not in practice. Comments focused on the uncomfortable and effortful nature of it ('for long questions, it might hurt my hand'; 'I don't think it's very practical'; 'it's smarter the other way').

Overall Experience. At the end of the session, participants were asked to rate their overall experience of the squeeze gesture along several satisfaction scales (Figure 4). Ratings were uniformly positive, but comments focused on concerns about false-positive triggering (even though this was only experienced by one participant during the study).



(a) A module installed into the left sidewall.



(b) The steel plates inside each module.

Figure 5: The sensor module of a Google Pixel 2 XL device.[1]

Summary

This study lends support to the concept of Active Edge and provided insights that informed the subsequent design of the hardware and interaction. In particular, in comparison to the status quo, squeezing a device can be an easy, comfortable, and reliable input method within the right ergonomic and use-case contexts. Ergonomically, users should be able to squeeze without adjusting or straining their hand posture, and without excessive or continued force. Similarly, the gesture's design should be distinctive and simple to trigger, and should not interfere with the task (either by harming its user experience or through false-triggering).

4 ACTIVE EDGE HARDWARE

Unlike the prototype, the production Active Edge hardware consists of two strain gauge modules adhered to the inner sidewalls of a device chassis (Figure 5a). A strain gauge measures the mechanical strain (ϵ) using conductors that change their electrical resistance when deformed. By adhering a strain gauge directly to an object, forces upon it can be measured without interference (i.e. unimpeded through insulating material). Strain gauges are both more sensitive inside a rigid chassis and more reliable at scale than comparable technologies reviewed in Section 2. However, their sensitivity is concentrated around narrow sensing elements.

A strain gauge's relationship between mechanical strain and electrical resistance is its *gauge factor* (GF):

$$GF = \frac{\Delta R/R}{\epsilon} = \frac{\Delta R/R}{\Delta L/L}, \tag{1}$$

where ΔR and ΔL are the change in resistance and length, respectively, from some unstrained state R and L.

As a phone chassis is designed to be rigid, the strain from a user squeezing it is extremely small ($\approx 1\,\mu\epsilon\,\mathrm{N}^{-1}$). To ensure reasonable sensing coverage each module contains three sensing elements along its length. Each sensing element is constructed from four printed carbon resistors arranged electrically in a Wheatstone bridge (Figure 6) and arranged physically on a flexible printed circuit that is wrapped around a set of steel plates (Figures 5b and 7).

When a user applies force to the sidewall of a device near the centre of a sensing element, the module bends with the inward flex of the sidewall. The steel plates act as the leaves of a hinge, placing the resistors pinning them under tension on one side and under compression on the other. This changes the electrical characteristics of the resistors, which

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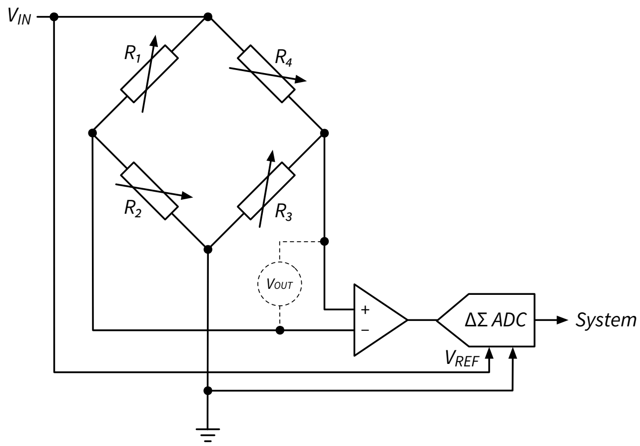


Figure 6: The electrical arrangement of a sensing element: four variable resistors in a Wheatstone bridge connected to an amplifier and an analogue-to-digital converter.

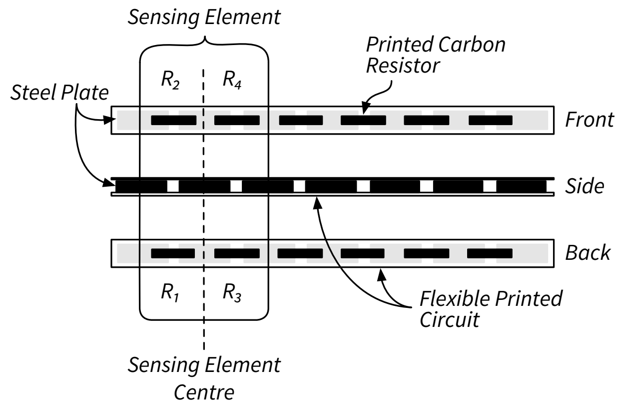


Figure 7: The physical arrangement of sensing elements on a module (cf. Figure 5).

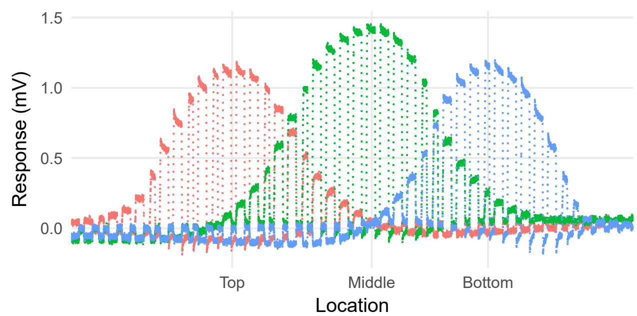


Figure 8: Sensing element responses to a 10 N force stepped down the side of a device (cf. Figure 5).

is expressed as a change in the voltage measured across the Wheatstone bridge (V_{OUT}; Figure 6):

$$V_{OUT} = V_{IN} \cdot \left(\frac{R_3}{R_3 + R_4} - \frac{R_2}{R_1 + R_2} \right). \tag{2}$$

Given a shared, constant unstrained resistance R, each resistor $(R_1, \ldots, R_n)$ has a value under some strain ϵ_n of:

$$R_n = R + \Delta R_n = R \cdot \left(1 + \frac{\Delta R_n}{R}\right) = R \cdot (1 + GF \cdot \epsilon_n). \tag{3}$$

Therefore, to maximise sensitivity, R_1 and R_3 should move together, and in opposition to R_2 and R_4.

Each sensing element is connected to a channel on an analogue front end that amplifies and encodes the sensed voltage level digitally.

The sensitivity and response characteristics of each sensing element is highly dependent on the design of the chassis and the assembly of the final device. For example, additional support material (e.g. a boss or rigid element) can reduce the sensitivity of nearby sensing elements or introduce aberrant response characteristics (e.g. non-linearities). A manufacturing process using known locations and forces is therefore required to calibrate the features of each sensing element so its signal can be standardised.

Signal Characteristics

The sensing elements have no stable reference point. Even when there is no force on the sensors, temperature changes will cause the measured voltage to drift. The remaining electrical noise is a stationary process. When a 10 N point load is applied directly to each sensing element location, the signal-to-noise ratio[2] is typically between 4 and 16. As noted above, this is dependent on the design of the device chassis surrounding each sensing element, and the assembly process. The high-frequency electrical noise from the system and low-frequency drift are well-separated from that of user inputs and can be removed with a band-pass filter to produce a dynamically-baselined signal.

The response is linear within 0–20 N, and as a force moves away from the centre of a sensing element the signal exhibits a Gaussian fall-off (Figure 8). Near-uniform sensor response is therefore achieved by minimising the ratio between the peaks and intervening local minima.

5 GESTURE & INTERACTION DESIGN

The goal of Active Edge is to offer users an easy and natural way to trigger device functionality when they *intentionally grasp* their device. As established in the earlier qualitative study (Section 3), the gestures that define an intentional grasp must be simple and ergonomic enough to encourage discovery of the feature and support continued use, while also being distinct enough to prevent confusion with other interactions (e.g. handling of the device).

[2]The mean signal at 10 N to the standard deviation of the noise at 0 N.

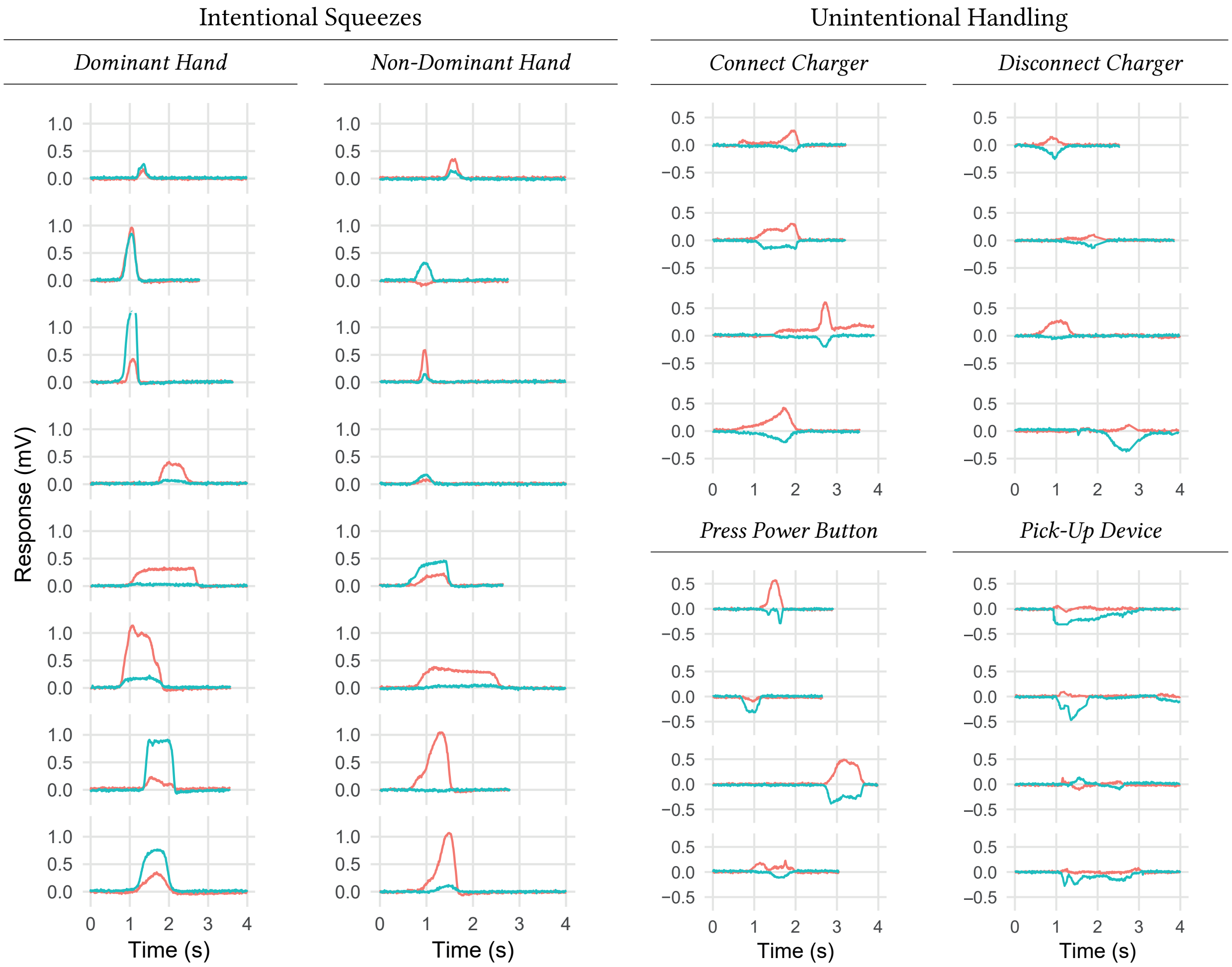


Figure 9: Selected samples from the open-loop data collection. For clarity, each line shows the response of only one sensor from each side of the device (blue: left; red: right). Dominant/non-dominant samples are pairs from the same participant.

Our focus is on a single squeeze gesture – however, *squeeze* is not a sharply defined term. It at least implies an increase in force around an object, but nothing about its magnitude or temporal profile. On physically malleable objects or a mechanical switch, the deformation of the object or actuation of the switch informs a user's force through tactile changes – but the rigid body of a phone chassis does not provide any such feedback. This means consideration must be given to: (1) the natural intuition of users when asked to 'squeeze' a phone (their *squeeze pattern*), and (2) how feedback can be used to guide users towards a gesture that is natural and comfortable to perform, but also robust to detect.

Open-Loop Data Collection

To inform the design of a squeeze pattern we conducted several open-loop data collection sessions. The goal of these sessions was to collect sensor data from users when asked to squeeze a device to trigger an action, but without any feedback from the system. The resulting profiles provided insight into how users interpreted the verb *squeeze* in terms of their force profile and hand position. The sessions also collected data from users holding and handling a device ordinarily, allowing us to compare patterns of *unintentional handing* with *intentional squeezing*.

As there were several rounds of these sessions during the design process, this section summarises the protocol and presents an overview of the major findings.

Participants. Approximately 20 participants participated in each session from the same demographic pool as the earlier study (Section 3). Participation lasted approximately 45 min.

Procedure. Using a phone with production hardware (Section 4), participants performed a series of actions in a random order that were categorised as either *intentional squeezes* or *unintentional handling*. Approximately 12 samples of each were collected. Unlike the earlier qualitative study, participants received no feedback on their actions.

Intentional Squeezes. Participants were presented with a scenario (e.g. 'imagine that this device will trigger a voice assistant if you squeeze it', 'imagine the alarm went off and you want to silence it') and a task to perform (e.g. 'ask for directions to San Francisco', 'squeeze the phone to silence the alarm'). The phone was placed on a table for half of the scenarios, and in the participants' hand for the other half. When placed in their hand, participants were asked to hold the phone as naturally and comfortably as possible, and to perform the tasks with both their dominant and non-dominant hands.

Unintentional Handling. Participants were presented with a scenario (e.g. 'imagine you are leaving your desk for lunch') and an action to perform would produce forces on the sides of the device (e.g. 'pick up the phone and plug it into a charger', 'pick up the phone and put it into your pocket', 'press the power button to turn the screen off').

Results. Although statistical analyses of the collected data were used, the most informative findings came from simple visual inspection of the data. This allowed broad trends to be quickly identified, with cognisance that feedback could be used to mould user behaviour (discussed later). Figure 9 shows selected samples illustrating the trends and variance.

Intentional Squeezes. There was substantial variance in the measured force between participants during intentional squeezes. The sources of this variance include participants' natural grip strength and disposition, but also the position of their grip relative to the sensing elements. However, the onset and removal of force (its velocity) were typically sharp – forming a clear peak or plateau in their pattern.

Very rarely were forces of a similar magnitude observed on both sides of the device. In most cases, a substantial signal on one side was opposed by either a reduced or negligible signal on the other. This is due to differences in the parts of participants' hands that applied and opposed their squeeze forces. Specifically, it was rare for a participant to squeeze using all of their fingers and palm evenly – rather, most of the force would come from one or two fingers, and the bottom corner of the opposing side would be pushed into the base of their palm (where there is no sensor coverage). The result was a substantial signal on only one or two sensors, and weaker or negligible signals elsewhere (e.g. Figure 1).

The time between the onset of force and its removal was generally brief (less than 0.5 s), but varied substantially. Much of this variance can be attributed to the open-loop nature of the procedure: without any confirmation feedback from the system, participants were unable to moderate their duration.

Unintentional Handling. Incidental interaction with the device also produced measurable forces on the sensing elements. Although these forces were generally lower in magnitude, they were still within the range of some participants' intentional squeezes. Many of the profiles also resembled reasonable intentional squeezes. However, the velocity of the force onset and removal was generally slower and noisier – lacking the sharp transition noted above.

These interactions also produced negative responses from the sensing elements. While a positive response is produced from the device chassis flexing inward, a negative response is produced from it flexing outward. For example, pushing on the volume buttons can cause the top of the chassis to bow inward and the bottom to bulge outward.

Squeeze Gesture Recognition

The open-loop data provided insight into the basic pattern of users' squeezes, and highlighted the areas of variance that need to be accommodated. In particular, intentional squeezes (1) are of a short duration, (2) have a sharp rise and fall in force, (3) have a large variance in magnitude, and (4) are not uniform across sensing elements or between sides.

From these insights we developed a gesture recognition algorithm that matched a sensor's signal to a characteristic profile using a set of parameters that could be scaled to each user's preference and ability. Figure 10 shows the principal components of this algorithm on such a profile.

In general, the algorithm looks for a rise and fall of force that occurs within some time window on any one sensor.

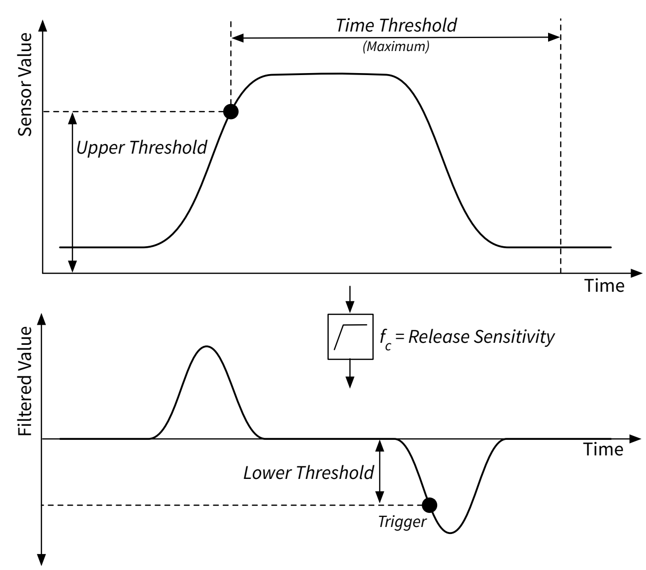


Figure 10: The principal components of the gesture recognition algorithm on a prototypical input signal: a rise and fall of a force within a time threshold.

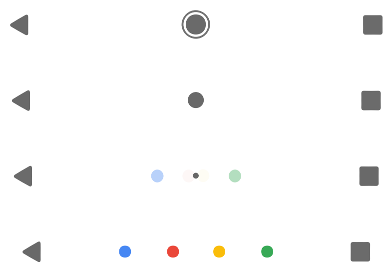


Figure 11: Navigation bar squeeze feedback (see Figure 1). The shrinking centre button and inward motion of the flanking buttons is designed to reinforce a *squeeze* action.

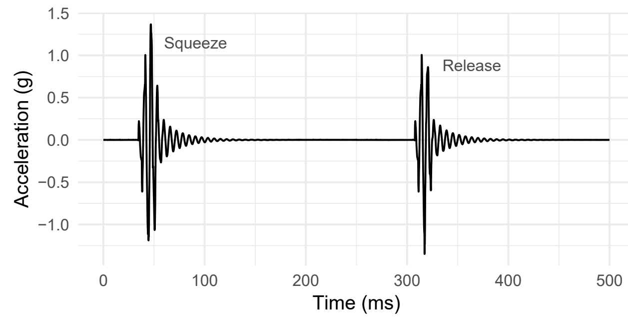


Figure 12: The acceleration response of the haptic feedback on a Google Pixel 2 when a user squeezes and releases; measured near the bottom of a device.

However, simply looking for a rise and fall of force is insufficient to discriminate an intentional squeeze from certain handling forces (e.g. picking-up the device). We therefore examined the velocity of the fall as a signal of intentionality. To parameterise this we used a high-pass filter with an aggressive cut-off frequency to tune its sensitivity to force changes, with a threshold to detect a true *release*.[3]

With the exception of the time threshold (presently, 1 sec), the default parameters of this algorithm were tuned for each device (forces were observed to be lower on larger devices). Initial tuning was against the open-loop data, and then later against closed-loop user feedback (described later).

Using a simple threshold-based heuristic algorithm allowed us to accommodate the variance in users' squeeze performances, and trivially tune it based on user feedback. A high level of accuracy and quality could be achieved without a large volume of training data and could be rapidly adjusted with new hardware revisions.

To further guard against false-positive detections, we also leveraged contextual information from other sensors on the device. For example, when the physical buttons on the device are pressed or a charging cable is inserted/removed, the squeeze-detection algorithm is gated for a short period.

Feedback Design

Feedback is a critical part of any gesture's design, particularly during the formative parts of a user's experience. For grasp gestures, feedback aims to (1) aid discovery of the feature, (2) assist users in learning the components of the gesture, (3) communicate the state of the system, and (4) create a psychophysical connection with the interactive surface.

Visual feedback is the only continuous feedback channel available (i.e. it can be updated *pari passu* with the input) and therefore enables discovery and experimentation with the gesture. To be minimally intrusive but globally available we used a progressive animation in the device's navigation bar (Figure 11). The elements smoothly animate as a proportion of the user's progress towards the upper threshold (Figure 10) and become fully-actuated when the threshold has been met. This crescendo is a signal to the user that they can now relax their grasp to trigger the gesture.

We also wanted to create a psychophysical sensation of compliance in the traditionally rigid surface – as if the sides of the device were actuating [e.g. 57, 60]. This was achieved using the haptic actuator on the device to perform two crisp haptic impulses at the inflection points of the user's squeeze to mimic the states of a physical switch: a robust sensation when the switch actuates, and a gentle sensation when it is released and resets. These impulses were created by driving the linear resonant actuator (LRA) with a square wave at its resonance frequency (155 Hz in this case) for 8 ms at the point of actuation (when the upper threshold was met) and for 6 ms at the point of release (when the gesture was triggered). Each impulse was followed by a closed-circuit active braking control to suppress its resonance ringing. Figure 12 shows the acceleration output of this effect.

The haptic feedback also helped to promote a transition to open-loop gesture performances that do not require continuous tracking of the visual feedback. That is, users could develop a muscle memory for the squeeze pattern trained through its haptic sensation.

Design Validation

To accommodate the variance observed in the open-loop data, users are exposed to a sensitivity control during a short on-boarding session the first time Active Edge is activated (Figure 13; and also later in the device's Settings application). The control is a nine-point slider from 'light squeeze' to 'firm squeeze', with its default in the middle. The range of the slider affects an approximately ±50% adjustment to the upper threshold of the algorithm.

[3]Experiments using a similar approach on the rising edge was too dexterously demanding for some users and was a barrier for discovery.

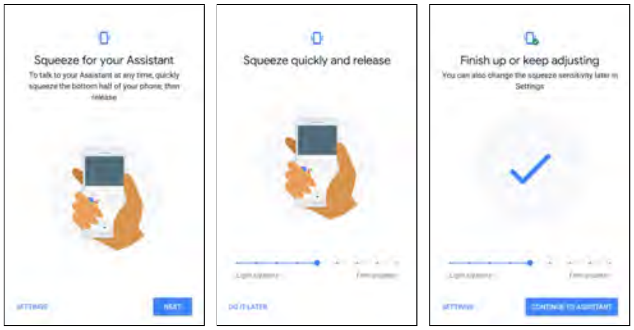


Figure 13: The onboarding process shown to users upon their first successful squeeze. Users must squeeze successfully to progress, and can configure the sensitivity.

The design of the algorithm, its feedback, and their parameters were tuned and validated on a pool of several hundred internal volunteer testers. Volunteers were selected to cover a broad range of user demographics, and were testing the devices generally (i.e. not specifically for Active Edge). Their feedback was critical to validate that the gesture was broadly accessible, was not intrusive on other device activities, and that the default parameters were balanced.

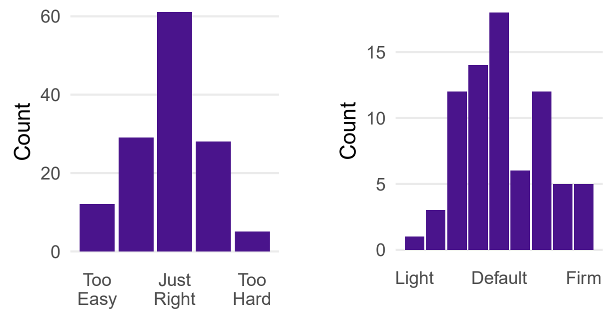
Near the end of development, a survey was sent to these testers to measure their satisfaction with the gesture design and the range of configurability offered. The survey asked:

- How does the default trigger sensitivity feel? (Five-point scale from 'too easy' to 'too hard'.)
- Have you adjusted the sensitivity (in Setup or Settings)? ('Yes'/'No'.)
  - If so, which setting did you change it to? (Nine-point scale, as above.)

The results shown in Figure 14 indicate that the chosen default parameters were balanced across the population of users, with no bias in either direction. Approximately half of the respondents indicated they had adjusted the sensitivity (52.6%; $n = 135$), and most users found a position within this control that satisfied their preference and ability (i.e. there was no obvious ceiling or floor effect).

Freeform comments reinforced these findings ('This works really well now! No accidental triggers, and the default pressure is just right.'; 'I adjusted the sensitivity, observed that it changed, and changed it back because the default was good.'), and were positive about its ability to reduce the friction for accessing device functionality ('my favorite way to access [the Google Assistant]';[4] 'it seemed gimmicky at first, but I find myself using it as my default way of accessing [the Google Assistant]') – but noted some areas of difficulty, particularly with car mounts that grab both sides of a device.

[4]Launching the Google Assistant is the primary action of Active Edge.



(a) How does the default trigger sensitivity feel? ($n = 135$)

(b) Which setting did you change [the sensitivity] to? ($n = 76$)

Figure 14: Response distributions to the sensitivity survey.

6 DISCUSSION

Since its release (October 2017), users have performed multiple millions of squeezes per day across all Google Pixel 2 devices (with 37.5% of those when the device's screen is off – supported solely by the haptic feedback), and squeezing is the predominant method for accessing the Google Assistant.

Although Active Edge is currently defined by a single gesture (a squeeze), the sensitivity of the hardware and its robustness suggest that this interaction space can continue to evolve. We deliberately focused on the design of a simple and satisfactory squeeze gesture, and are actively exploring expansion of its functionality while retaining its simplicity.

However, we are cautious about gestures where the level of force is a parameter given the large variance between users in their natural grasp ability, and the difficulty users have in controlling their force without strong visual feedback [49, 64]. Similarly, each new gesture requires complementary feedback to create a closed control loop with the user. Even training users on the squeeze gesture for Active Edge was challenging as they did not always form a feedback connection between the system's response and their actions (specifically, the need to release their grasp).

Advances in haptic technologies also support the development of this interaction space by enhancing the tactile information that users can receive. Current actuator technology cannot produce continuous feedback without adverse resonant effects and was limited to discrete impulses for Active Edge feedback. New actuation or stimulation techniques may allow the generation of continuous tactile responses (e.g. softness or malleability as the user's grasp force increases) or passive surface texture sensations (e.g. the location of active areas as the user slides over them [33, 36, 59]).

The sensing technology itself is also capable of detecting how a user is handling the device (Figure 9), which can provide contextual interaction cues (e.g. handedness and orientation [5, 67]). Similarly, signals related to moving the device (e.g. picking it up or removing it from a pocket) may produce distinct enough force profiles to be sensed as their own gestures.

The interaction vocabulary in mainstream consumer products tends to be small, conservative (rather than innovative), and resistant to change [7, 37]. Expanding that vocabulary beyond pointing and scrolling (and their mobile counterparts: tapping and swiping) has long been a pursuit of human–computer interaction research. Against that backdrop, we took squeeze gestures from conceptual explorations, prototype-based empirical studies, and human factors engineering to integrate it into a mainstream consumer product. This paper has summarised the key elements of that journey.

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