

# Theoretically-Defined vs. User-Defined Squeeze Gestures

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This paper presents theoretical and empirical results about user-defined gesture preferences for squeezable objects by focusing on a particular object: a deformable cushion. We start with a theoretical analysis of potential gestures for this squeezable object by defining a multi-dimension taxonomy of squeeze gestures composed of 82 gesture classes. We then empirically analyze the results of a gesture elicitation study resulting in a set of  $N=32$  participants  $\times$  21 referents = 672 elicited gestures, further classified into 26 gesture classes. We also contribute to the practice of gesture elicitation studies by explaining why we started from a theoretical analysis (by systematically exploring a design space of potential squeeze gestures) to end up with an empirical analysis (by conducting a gesture elicitation study afterward): the intersection of the results from these sources confirm or disconfirm consensus gestures. Based on these findings, we extract from the taxonomy a subset of recommended gestures that give rise to design implications for gesture interaction with squeezable objects.

CCS Concepts: • **Human-centered computing** → **Gestural input**; **Graphical user interfaces**; *Interactive systems and tools*; • **Software and its engineering** → **Graphical user interface languages**; Runtime environments; • **Computing methodologies** → *Model development and analysis*.

Additional Key Words and Phrases: Deformable User Interfaces, Design Guidelines, Gesture Elicitation Study, Gesture User Interfaces, Shape-Changing Interfaces, Squeezable object, Wearable computing

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## 1 INTRODUCTION

Shape-changing interfaces (SCI) [68] offer new types of interaction paradigms where the end user is interacting with a digital object whose form can change depending on the user actions. Such objects serve both as input (e.g., when a user presses on an object) and as output (e.g., when resistance is provided by force feedback or vibrotactile feedback). In the largely expanding family of SCI, *Squeezable User Interfaces* (SQUIs) [36] materialize interaction based on a tangible object whose any deformation indicates sources of input, therefore suggesting that deformation applied

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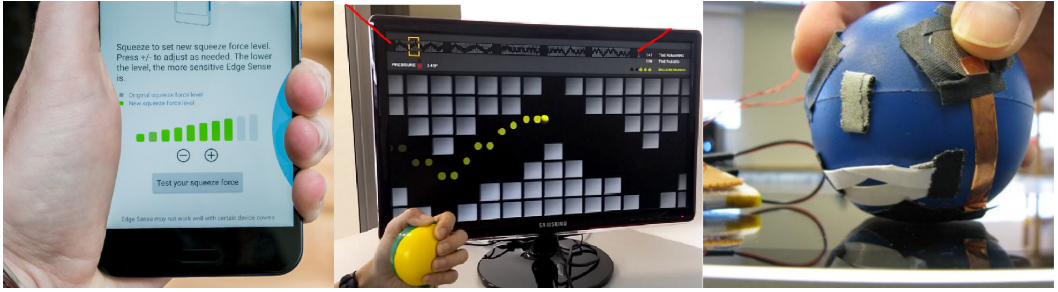


**Fig. 1.** Squeezable objects afford a wide variety of touch, gesture, and tangible interaction: (a) HTC U12+ with EdgeSense; (b) a squeezable ball for moving a target on a display [24]; and (c) Skweezy, a squeezable ball with three pressure points for multi-dimensional force input [81].

on any portion of the object is more prioritized in this interaction paradigm. Deformation can take several forms, such as [59]: pressing/depressing or squeezing [36, 70], stretching [63], pinching [59], folding/bending [10, 31], moving around [66], and any surface/volume deformation [28].

Squeezable objects offer new interaction opportunities: they can combine touch interaction (e.g., pressing on a certain part of the object), gesture interaction (e.g., issuing a gesture with some part of the object), and tangible interaction (e.g., by manipulating the object in space). Three main parts of a squeezable object can be synchronously and concurrently exploited: the surface of the object, the volume of the object, the motion of the object, and the capabilities of the object to be subject to deformation by pressure. Hence, a squeezable object is able to afford gestures that are candidates for surface computing (the surface of the object is used as a classical interaction surface [58]), for volume manipulation by deformation (the volume of the object is exploited for initiating a gesture), and for motion (the object itself moves in space and indicates a gesture).

For these reasons, many SQUIs applications appear both in research [70] and in industry [22]. A noticeable one is HTC's U12+ smartphone equipped with EdgeSense (Fig. 1a), where all edges are sensitive to pressure to generate squeeze gestures, even when the smartphone is switched off.

While squeezable interaction technology is currently being developed at a high rate, the majority of effort has been put into physical development and industrial design, and less on algorithms to recognize squeeze gestures, apart a few [48, 64]. Most SQUIs are designed and developed for a very specific and narrow purpose, thus offering little or no generalization of their results and capabilities to a wide spectrum of SQUIs. And so are the squeeze gestures that are shipped with them. These gestures are often limited in number (6 to 8), in design (they are very similar to classical gestures and do not exploit the full potential of pressure), and system-defined (the device imposes its own set of gestures) [45]. No thorough analysis has been conducted on *user-defined preferences for squeeze gestures* and, consequently, there is little information available to

- (1) *Designers and practitioners* about what types of squeeze gestures to utilize for which tasks.
- (2) *Manufacturers* with regard to user-defined gestures to include in the future versions of their squeezable objects as opposed to their system-defined ones.
- (3) *Researchers* to systematically analyze users' squeeze gestures.
- (4) *End users* on how to customize their squeeze gestures whether the device permits.

This work represents the first investigation to inform gesture SQUIs design for squeezable objects by providing insights and implications for design resulting from a theoretical systematic analysis and an empirical elicitation study. To this end, the contributions of this work are as follows:

- (1) We conduct the first scientific investigation to collect, analyze, and understand participants' preferences for squeeze gestures. Our practical results consist in:

- A theoretical analysis of squeeze gestures based on the notion of dimension which gives rise to a theoretical taxonomy of potential gestures.
  - An empirical analysis of squeeze gestures resulting from a gesture elicitation study.
  - A further characterization of squeeze gestures along classical factors (e.g., agreement rate, action, and locale) and two new factors (i.e., dimension and mechanoreceptor) to analyze and inform squeeze gesture design.
- (2) We also contribute to the classical gesture elicitation methodology [77, 85, 86] with insights on how theoretically defined squeeze gestures could inform empirically derived ones.
  - (3) From our findings, we derive some implications for designing squeeze gestures.

## 2 RELATED WORK AND BACKGROUND

This section gives an overview of prior SQUIs work done with a focus on gesture interaction. Then, it discusses the methodology [77, 78, 86] employed to conduct a Gesture Elicitation Study (GES) [85] for collecting and analyzing user-defined squeeze gestures.

### 2.1 Squeezable Interaction

We hereby define *squeezable interaction* as interaction technique where exerting a pressure or a depressure on a tangible object results in changing the shape of this object which is interpreted as a source for interaction input/output. Squeezable interaction is interesting for several reasons.

*Grasping*, i.e., closing the hand when something touches the hand palm, is an *innate gesture* that any newborn possesses since birth [33]. When the cortex of the human brain becomes mature enough, reflex grasping is progressively replaced by explicit *grabbing* by squeezing around the age of 4 months, as an *acquired gesture*. Since this time, human being has the capability to control squeezing gestures by the cortex, thus explaining why they are used in our daily life (e.g., to press fresh juice from oranges, to get some sauce out of its tube, to shake a hand to say “hello” and “goodbye”, to press somebody’s forearm to attract attention).

*Squeezing* can require some particular training within an interaction design context, but not in general. Squeezing is care-free, but generates fatigue [36]. Our fingers are the most precise limbs for prehension, for applying pressure on objects, thereby explaining why playing piano is achieved through our fingers (for location, combination, and fine pressure).

### 2.2 Examples of Squeezable User Interfaces

We now review selected, representative examples of squeezable interaction.

**Puyo-Con** (Fig. 1b) [24] is a ball-shaped, soft, and wireless controller that users can roll, throw, squeeze, or move with both hands to perform a task, such as moving a cursor. Based on 14 pressure sensors and a three-way acceleration sensor, it supports touch, force, and shape-changing interaction. **Squeezy** (Fig. 1c) [81] is soft device equipped with three force sensing resistors mounted on a rubber ball that capture force input and provide passive haptic feedback.

**Skweezee** [70] is a complete system for deploying squeezable user interfaces, based on soft squeezable object filled with conductive padding (Fig. 2a) and electrodes, an electronic circuit (Fig. 2b) and software to define and record squeeze gestures (Fig. 2d-i) for various squeezable objects (Fig. 2c). Based on this material, members of the Doing-It-Yourself (DIY) community can bring their plush or any other object candidate to the Skweezee Studio [18] and convert it into a working squeezable user interface. This has been successfully applied to occupational therapists [42].

**SqueezeMe** [39] is another system for deploying squeezable user interfaces where an interactive cover for a tablet or a smartphone is made of a soft rubbery material with pressure sensors. It can be squeezed with both hands. The intensity of the input is reflected in the output.

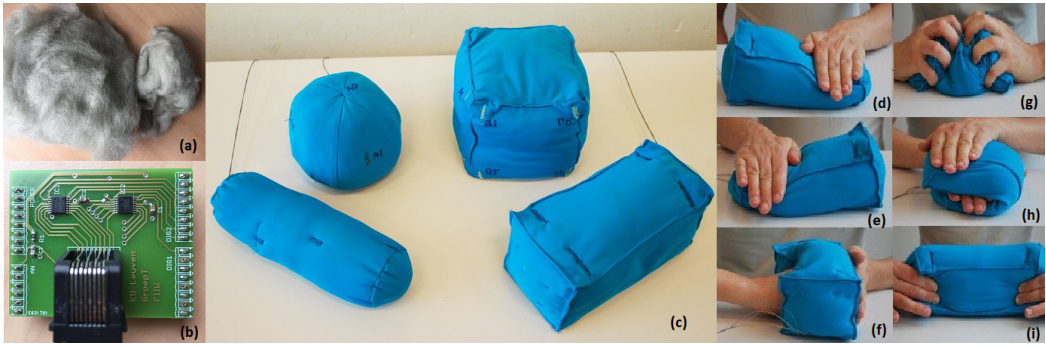


**Fig. 2.** The Skweeze system [70] that is used in our study: (a) stuffing with conductive filling, (b) electronic circuit, (c) four Skweezes: a sphere, a cube, a cylinder, and a cuboid, and squeeze gestures on the cuboid: (d) left squeeze, (e) right squeeze, (f) punch squeeze, (g) crumple, (h) sandwich, (i) stretch.

**HandLog** [5] is a squeezable device that supports single handed deformation through finger flexion as a continuous digital input. By measuring resistance changes across the conductive foam columns of the object during deformation, hand or finger flexion motions are mapped to tasks.

**SqueezaPulse** [23] is a squeezable device using soft, passive, low cost bellow-like structures in which, when squeezed, air pulses travel along a pipe and into a corrugated tube to form recognizable sound signatures transformed into input for interaction. **Flexibles** [60] are squeezable objects placed on capacitive touch screens to capture different types of deformation. They are mapped to mechanisms like pressing, squeezing, and bending input with multiple levels of pressure.

Lee *et al.* [36] introduced a design space for characterizing squeezable interaction along two dimensions: (1) *magnitude*, which represents the kinds of vertical pressure a user's hand is applying to an object and what cues the system receives from it: this magnitude can be binary (squeezed or untouched), discrete (squeezed repeatedly) or continuous (squeezed without stopping); and (2) *region* whether or how the different regions on the object surface receive the pressure/depressure and react accordingly: no region when the whole object can be squeezed, spots when only some points are sensitive to pressure, defined regions when some regions are dedicated to pressure, and continuous. We refer to this paper for a more comprehensive review of SQUIs.

### 2.3 Squeeze Gestures

**FlexiBend** [10] is a strip built upon a continuous array of strain gauges capable of sensing shape changing locally or globally. Squeeze gestures include shape recognition (*e.g.*, a spiral), twisting, stretching, and bending. **SqueezeDiary** [11] is a squeezable ball pressed when an end user records a time-space diary event (*e.g.*, “I was here”) into the smartphone and for describing the triggers later when the user becomes available again. As such, only one gesture is needed: squeeze with the pressure level indicating the importance of the event *vs.* untouched.

**SqueezeTheMoment** [12] structures this process into three steps: record, review, and reflect. Marti & Iacono [40] compared a SQUI against a GUI: the short-term evaluation reveals that the “Squeeze to zoom” gesture was assessed with higher values than the “Slide to zoom” in the hedonic quality-stimulation and attractiveness dimensions, whilst it obtained lower values in the pragmatic quality and hedonic quality-identity. This progressively decreases with time.

**EdgeSense** (Fig. 1a) supports short *vs.* long squeeze gestures on regions around the smartphone edges such as: a short squeeze launches the camera, a corner squeeze takes a picture, a squeeze-and-hold gesture launches the voice assistant, a left *vs.* right squeeze gesture plays and pause the music player when active. squeeze gestures can be customized to assign specific tasks, such as turn

the flashlight on/off, start/stop voice recording, turn Wi-Fi on/off, expand/collapse the notifications. The system-defined gestures cannot be modified since the system does not support end users in customizing their own gestures.

**BendID** [47] is a bendable pressure-sensitive input device that recognizes the location, magnitude, and direction of its deformation based on SVMs. Only a few gestures were identified and discussed, such as “press lower right corner”, “press middle”, and “press upper middle”. **DeformWear** [83] is a tiny wearable squeezable device offering single-point deformation on various body locations. Despite the small surface, it enables expressive and precise input using high-resolution pressure, shear, and pinch gestures. In **Squish This**, Fruchard *et al.* [17] compared three levels of softness, *i.e.*, soft, medium, and hard, for a visual targeting task and reported that high force levels appear more demanding for soft surfaces, but that performance is similar to rigid surfaces, regardless of the compliance.

**Squeezy-Feely** [59] investigates whether an auxiliary finger input complements gestures, like squeezing the edges of a device, are feasible as an input modality. In particular, a thumb-index pinching can be an effective gesture on a deformable surface provided that spans of grip, counterforce, direction and scales of grips are determined according to their recommendations (*e.g.*, a large grip span, no top-to-bottom direction). **DigitSpace** [26] consists of a thumb-to-fingers SQUI investigating hand anatomy (which restricts possible movements of a thumb) and touch precision (which determines the precision required to manipulate touch widgets set on fingers). Their third study explored the optimal layout for touchpads for six stroke gestures (Graffiti letters) by considering input area and tactile cues.

Boem & Troiano [6] surveyed 131 papers on deformable interfaces and input to build a framework for “**Non-rigid HCI**”. We position our present work in relation to this framework in the category of hand-based deformable input (squeeze gestures are performed with one hand or two hands) applied on a geometric elastic shape. In this category, they list candidates for squeeze gestures: bend, squeeze, stretch, twist, and push are the most common. Stretch is less common compared to bend and squeeze. Twist is the result of bending with two hands in opposite directions and can be performed either vertically or horizontally. Push is used often for input on elastic surfaces.

Previous works on squeezable interaction and SQUIs have mainly focused on acquiring squeezable gestures in various configurations, with a limited set of gestures, whereas this paper focuses on uncovering a larger set of squeeze gestures and on better understanding which ones are preferred by end-users. An empirical investigation of these preferred gestures *vs.* a theoretical classification in a taxonomy aims at identifying the overlapping between these two approaches.

## 2.4 Gesture Elicitation Studies and its Method

Understanding users’ preferences and behavior with new interactive technology from the early stages of design empowers designers with valuable information to shape a product’s characteristics for more effective and efficient use. This process has a specific implementation in the literature in the form of “guessability studies” [85] or more recently “Gesture Elicitation Studies” (GES) [77, 78, 86] to collect and analyze users’ preferences for gesture input for a variety of contexts of use.

According to a systematic literature review [80], past ISS editions published several GES. Rodriguez & Marquardt [55] reported an overall preference for hand and arm gestures when people have to opt-in and out a public system, thereby raising the question of their social acceptance. Sukumar *et al.* [65] explored hand-drawn user-defined gestures for common text-editing tasks. Chen *et al.* [9] conducted a GES for ear-based input. Fingers, hands, and arms are the most frequent parts of the human body considered in GES [80], leaving other regions rarely covered, such as nose [50] or shoulders [69].

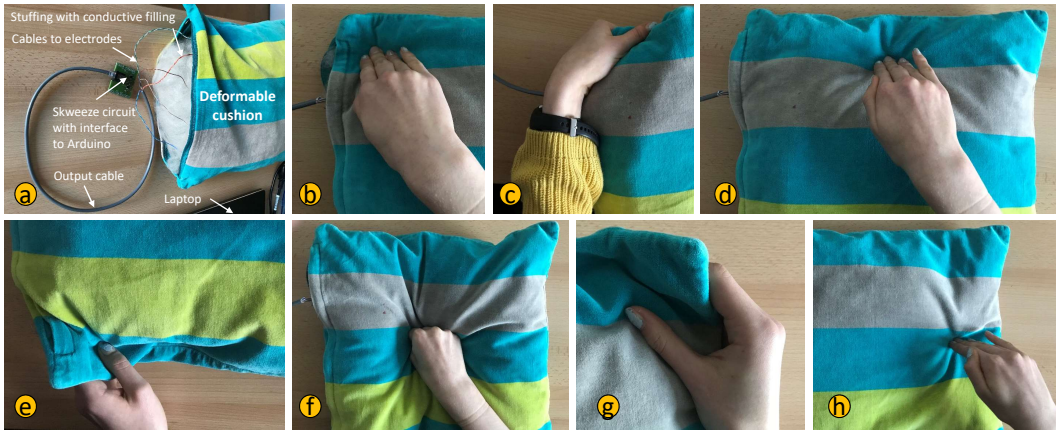


**Fig. 3.** Gesture elicitation study with the deformable cushion: (a) setup, and some squeeze gestures performed by participants: (b) a 4-point top left push, (c) a n-point dual-side top left corner press, (d) a 3-point top margin push, (e) a fold bottom left corner, (f) a crush, (g) a fold top right corner, and (h) a n-point right edge push.

Eight studies published user-defined gestures in past ITS editions: Seyed *et al.* [61] for multi-display environments, Frisch *et al.* [16] for editing diagrams on large displays, Buchanan *et al.* [8] for manipulating 3D objects, Grijincu *et al.* [21] for re-analyzing gestures for controlling a web browser, a word processor and an image editor, Morris [43] for controlling a web browser on a smart TV, Pyryeskin *et al.* [53] for above-surface gestures, Nebeling *et al.* [46] for replicating Morris' aforementioned GES [44], and Matsumura [41] for off-screen interaction.

## 2.5 Methodology for Conducting a Gesture Elicitation Study

The outcome of a GES consists in a characterization of users' gesture input behavior with valuable information for designers, practitioners, and end users with regard to the *agreement* or *co-agreement rates* [77, 78, 86]) between users. All GES rely on referents to prompt participants and to provide them with a simulated context of use, in which they could develop their mental model [71]. To maximize the learnability and the memorability of such user-defined gestures, Ali *et al.* [2] recommend visual priming of referents. We are wondering to what extent participants would propose the same gestures in an empirically-conducted GES as in a theoretically-determined taxonomy of these gestures. On one hand, a visually primed referent favour the elicitation process by guidance, but also restricts the scope of proposed gestures by sticking too much to the referent. Such an approach may keep the participant's mental model open to any gesture proposal, independently of any theoretical representation. Our underlying research question is therefore:

RQ = What are the similarities and differences between theoretically-defined squeeze gestures and empirically-derived ones from a GES?

## 2.6 Summary

Squeeze gestures have a lot of potential for a variety of contexts of use [36]: for different users and tasks [18, 42], with different types of devices [23, 47, 60, 83], for different environments and locations [11]. Prior work has focused almost exclusively on developing an effective and efficient technology for supporting squeezable interaction and for recognizing squeeze gestures. Since only a few such gestures were considered, squeeze gestural interaction design is still in its infancy. There is no systematic exploration of how squeeze gestures can be effectively designed and mapped to

tasks depending on the context of use. Thus, the community lacks relevant knowledge about *how to design intuitive squeeze gestures reflective of user behavior*. A solid, rigorous understanding of users' gesture preferences will therefore benefit all the aforementioned application domains. In this work, we make the first step towards such an understanding.

### 3 TAXONOMY OF SQUEEZE GESTURES

This section is aimed at defining an extensive taxonomy of squeeze gestures that should serve as a starting point for the empirical part. Instead of continuing with an *incremental approach* where new gestures are added opportunistically to other ones without any regular schema, we strive for a *systematic approach* [36], where the viability of the taxonomy is based on the experiential application of clearly defined and repeatable steps and an evaluation of the results. The goal of a systematic approach is to identify the most efficient means of generating a consistent and optimal taxonomy. This taxonomy will never be complete (new gestures will always be discovered), but will be consistent (all definitions are sound with respect to each other) and correct (all definitions effectively refer to the right gestures).

#### 3.1 Definition and Examples

First, we provide our working definition for a squeeze gesture:

A squeeze gesture is any pressure action exerted *with* or *on* a squeezable object, perhaps along with a movement of this object, that causes a detectable form change of any part of it.

By adopting this definition, we draw some inspiration from Shilkrot *et al.* [62], who distinguish two forms of input: *contact-based gestures*, which are performed on the surface of the device and usually mimic interactions common on touch screens, such as tap, pinch, or swipe; and *contactless gestures*, which are performed around the device without actually touching it. In this paper, we adopt a comprehensive approach by considering only gestures that incorporate pressure as an explicit intention in gesturing. Any other gesture not including any pressure action is discarded since it is then equivalent to a contact-based or contactless gesture. Thus, all the following examples are valid squeeze gestures for the purpose of this study (See Fig. 3 for more examples):

*Examples:* Press a squeezable once, twice, or multiple times in a row. Apply a rhythmic pattern on the surface. Rotate the squeezable with it in hand. Rotate the fingers wearing the squeezable. Rotate the hand wearing the squeezable. Slide a finger on the object's surface while pressing it. Push, pull out the object. Change the object to a different set of fingers, and switch the object from one hand to another. Any combination of the above.

In contrast, the following gestures are not considered squeeze gestures:

*Examples:* Touch the surface of an object once, twice, or multiple times in a row. Apply a rhythmic touch pattern on the object's surface. Drag an imaginary target on the object surface and drop it on another region. Scroll an imaginary object on the object surface. Flick among imaginary regions or swipe imaginary contents among these regions. Any combination of the above.

Gestures can be classified according to many criteria, such as: articulation time [35], binding [61, 72, 84, 86], complexity: elementary vs compound gestures [3, 35, 54, 56], contact type [61], distance [61, 89], flow [84, 86], form [84, 86], movement structure [54], nature or semantic meaning [35, 54, 56, 84, 86], symmetry [73, 84], temporality: parallelism vs sequentiality [30, 54, 56, 57], position [89], physicality [54, 79], planning time [35], velocity [3, 30, 89], and volume [30, 89]. Instead of classifying gestures based on these criteria at the first level, we organize them according

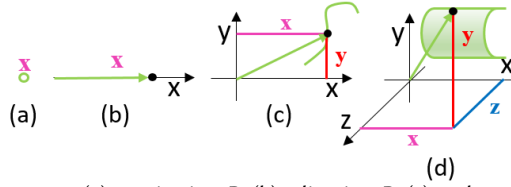


**Fig. 4.** Dimensionality of gestures: (a) a point in  $0D$ , (b) a line in  $1D$ , (c) a plane in  $2D$ , and (d) a space in  $3D$ .

to the *dimensionality* [20], hereby defined as the minimum number of coordinates needed to specify any gesture point. The dimensionality of a gesture remains an intrinsic property independent of the space in which the gesture is produced. Possible values are (Fig. 4):

- (1)  $0D$ : when no coordinate is needed. For example, a point has a dimension of zero because it either exists or does not exist.
- (2)  $1D$ : when one coordinate is needed. For example, a line gesture has a dimension of one because only one coordinate is needed to specify a point on it. Two points can be connected to create a line segment.
- (3)  $2D$ : when two coordinates are needed. A surface such as a plane or the surface of a cylinder has a dimension of two because two coordinates are needed to specify a point on it.
- (4)  $3D$ : when three coordinates are needed. The inside of a cube or a sphere has a dimension of three because three coordinates are needed to locate a point within these spaces.

The dimensionality was chosen as a first class citizen to organize squeeze gestures to satisfy the following principles: separation of concerns (any gesture can be classified in one and only one category), orthogonality (the union of all categories form a partition of the taxonomy), and fine granularity (the granularity is not too gross at the beginning to classify gestures).

*Augmented gestures* are common gestures augmented with additional properties forming new additional dimensions, such as pressure, point “width and height”, angle, velocity, or tangential acceleration. Therefore, squeeze gestures constitute a particular category of gestures augmented with pressure as an additional property, which can be used for different purposes, such as: to use pressure data associated with touch points to augment the gesture properties, to increase the gesture fidelity and to improve its recognition when using advanced pressure sensitive multi-touch input devices, but also differentiate among levels of pressure. Since pressure can be exerted on several regions, squeeze gestures are actually excellent candidates for an application that requires a wide spectrum of gestures, both planar and spatial. The main difference between squeeze and pressure-augmented gestures is that the former can be operated on any squeezable object, whether it is planar or volumetric, while the latter can be operated only on touch surfaces.

### 3.2 Defining and Exploring the Taxonomy

Figs. 5 and 6 present the results of the systematic analysis of squeeze gestures along their dimensionality. They are applied to the particular squeezable object that will be used later for the experiment: a deformable cushion based on the Skweeze environment [70] (see Fig. 3a for the setup).

**3.2.1  $0D$  Gestures.** In this dimension, squeeze gestures are restricted to issuing only one or several pressure points on the squeezable object. Based on the symmetry axes of the cushion when projected as a rectangle, 17 pressure regions can be univocally identified (Fig. 5, first part): the center, the four medians, the four diagonals, the four corners and the four margins (where they are located on the margin does not matter). The center, along with the symmetry axes, form the sub-category of inside gestures, while the four corners and the four margins form the second sub-category of edge gestures. We therefore define *inside gestures*, respectively *edge gestures* [49], as squeeze gestures that are issued inside any surface of the object, respectively outside, *i.e.*, on the edge of any surface of the

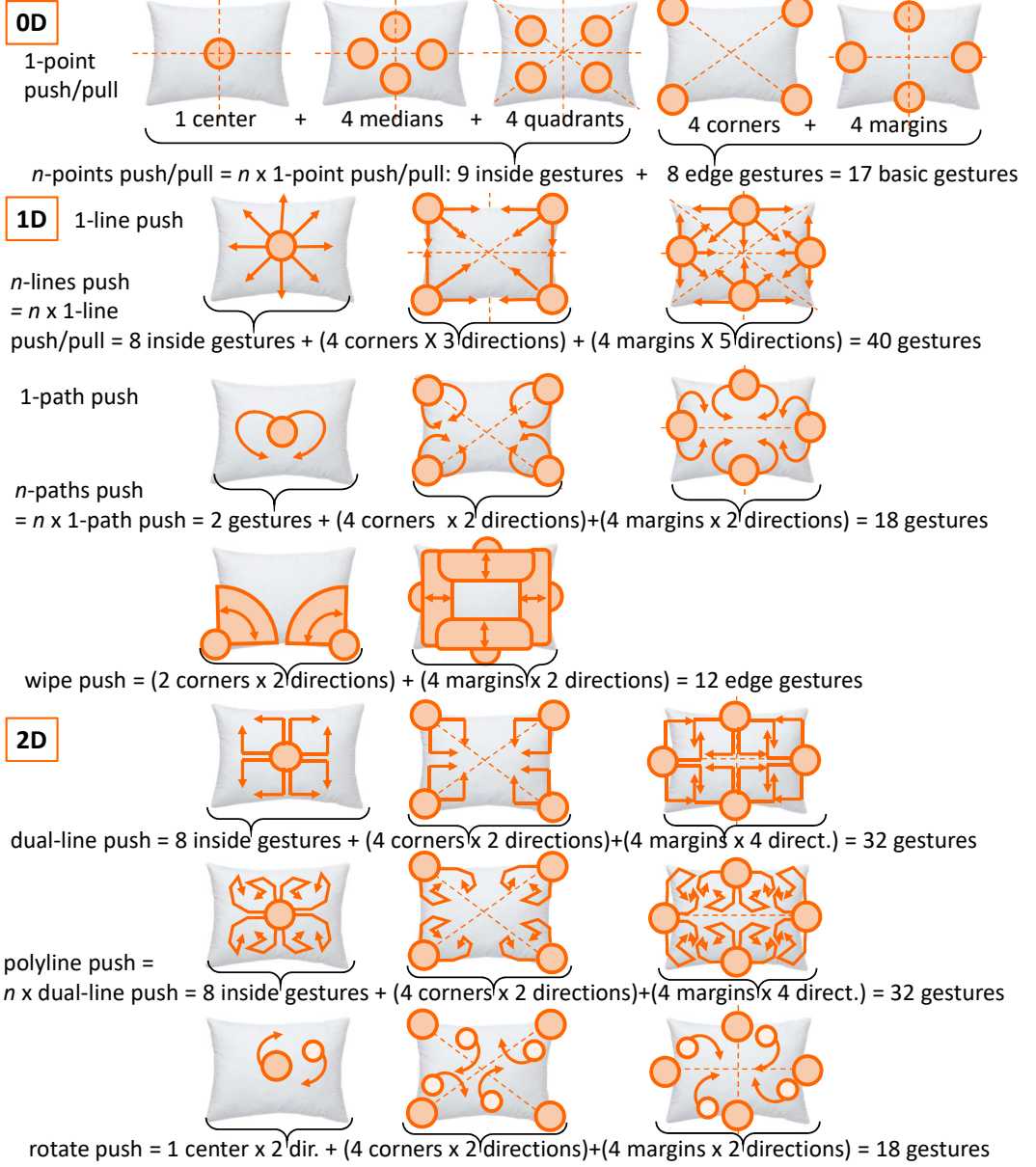


Fig. 5. Taxonomy of squeeze gestures: from 0D to 2D.

object. If a squeezable cube is considered, the four corners and the twelve edges would initiate edge gestures, while the others would generate inside gestures.

A **1-point push-pull** is a squeeze gesture consisting of a press + release on one region only, thus raising 9 inside gestures + 8 edge gestures = 17 basic gestures. Each gesture is said to be discrete, respectively, continuous, if and only if the release is achieved immediately, respectively, after a temporal threshold. A  **$n$ -point push-pull** generalizes it to a set of multiple regions, therefore offering 17 more basic gestures. The  $n$  pressing points can be produced indifferently by one or many fingers, one or two hands, which is why  $n$  is specified as a general value of multiplicity.

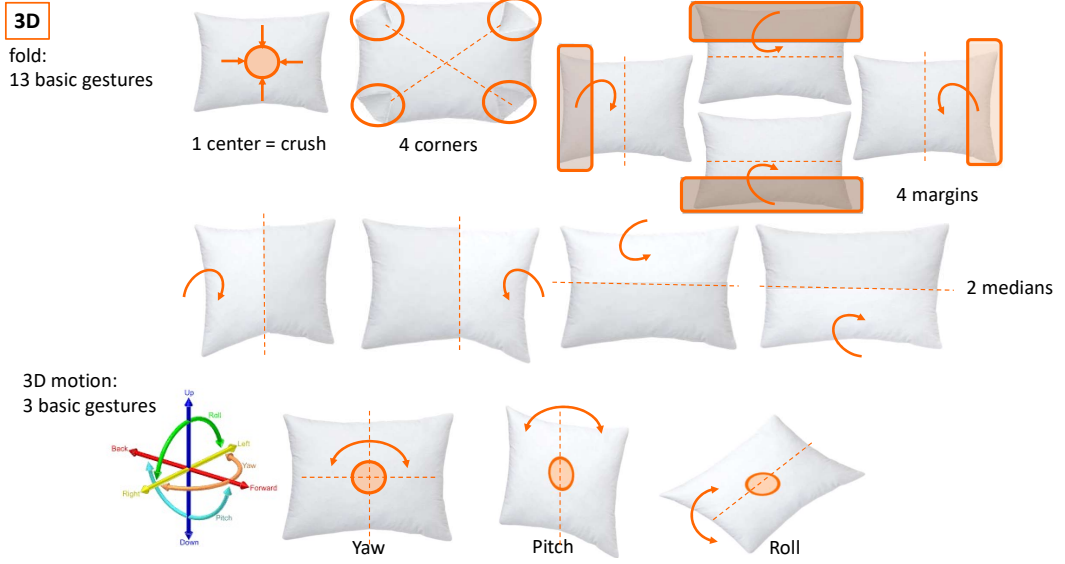


Fig. 6. Taxonomy of squeeze gestures: 3D.

A **hold push-pull** simply maintains the pressure after the temporal threshold, therefore raising 17 additional basic gestures for one region and 17 others for  $n$  regions, which makes 34 basic gestures. **Multiple push/pull** introduces the repetition factor: while a simple push/pull is a sequence of press+release, a multiple one repeats this sequence a certain amount of time, which produces again 34 more basic gestures. When a repetition follows a certain rhythm, for instance, three presses per second one or multiple times, the **rhythmic push/pull** introduced 34 more basic gestures. In total, the 0D dimensionality groups  $17 + 17 + 3 \times 34 = 136$  basic gestures.

In principle, any region can be pushed (by exerting pressure or attraction) or pulled (by exerting depressure or repulsion), on the front part, the back part or both (e.g., by pushing on one side of the object and pushing on the symmetric region on the other side of the object). For each region, we therefore define a basic gesture as any gesture that is dependent of the position, but independent from the *pressure direction* (i.e., push or pull) and the *face* (i.e., front, back, or dual-side). Each basic gesture therefore gives rise to 6 individual gestures: 1 basic gesture  $\times$  2 directions  $\times$  3 faces = 6 individual gestures. For 0D, we therefore have 136 basic gestures  $\times$  6 variations = 816 individual gestures, which already represent a large set of individual gestures.

To better characterize this variation, we rely on the notion of symmetry. *Symmetry* characterizes how the two hands are used to produce a gesture, with four categories: (a) *dominant unimanual* when the user performs a gesture using her dominant hand (right or left), (b) *non-dominant unimanual* when the user performs a gesture with the other hand, (c) *symmetric bimanual* when the user performs a gesture using both hands in symmetric and synchronous movements, and (d) *asymmetric bimanual*, when the user performs a gesture using both hands in different ways, possibly asynchronously. We adopted this criterion from Piumsomboon *et al.* [51], who used it to characterize users' mid-air gestures for augmented reality applications and which were subsequently used in other studies [30, 74, 89]. A forward or a backward gesture can consequently be unimanual (most of the time, e.g., Fig. 3), when one hand is involved, or bi-manual, when the two hands are involved. A dual-side gesture is likely to be a bimanual symmetric gesture as well, except perhaps for edge gestures, which may require only one hand for pressing both sides of the object concurrently (for instance, Fig. 3c is unimanual non-dominant and Fig. 3h is uni-manual dominant).

**3.2.2 1D Gestures.** In this dimensionality, squeeze gestures are restricted to press one or several straight or elliptic lines on the squeezable object. Based on the symmetry axes of the cushion, 9 pressure regions can initiate the gesture (Fig. 5): the center, the four corners and the four margins.

A **1-line push** therefore consists of: 1 center  $\times$  8 directions + 4 corners  $\times$  3 directions + 4 margins  $\times$  5 directions = 40 basic gestures. The **n-lines push** add 40 basic gestures in the same way. When the straight line is replaced by an elliptic line, whose path is regulated by a mathematical analytical function as opposed to any 2D path, the 1-path and the n-paths push both consist of: (1 center + 4 corners + 4 margins)  $\times$  2 directions (clockwise and anti-clockwise) = 18 basic gestures.

An original family of gestures that was revealed in the informal inquiry is the **wipe push**: some participant produced a gesture imitating a car screen-wiper while pushing on the object. Hence, the wipe push consists of: 2 corners (bottom left and bottom right only, because the human elbow cannot reach the top corners for the same gesture)  $\times$  2 directions (clockwise and anti-clockwise) + 4 margins  $\times$  2 directions = 12 basic gestures. When initiated from a corner, the wipe follows an angular path with the forearm rotating; when initiated from a margin, the wipe follows a lateral path with the forearm keeping the same angle. In total for 1D, we therefore have  $40+40+18+18+12=128$  basic gestures  $\times$  3 variations (i.e., front, back, or dual-side) = 384 individual gestures, which again generate another large set of individual gestures. In this dimension, only push gestures can be initiated along a path in front of the object and only pull gestures in the back, as opposed to 0D gestures where any point can be pushed or pulled (e.g., by pinching it).

**3.2.3 2D Gestures.** In this dimension, squeeze gestures are restricted to press only one or several curves of different types on the squeezable object. Based on the symmetry axes of the cushion, 9 pressure regions can initiate the gesture (Fig. 5): the center, the four corners, and the four margins. When initiated on the front of the object, the gesture consists of a push (the pull is impossible), while on the back it consists of a pull towards the person.

A **dual-line push** therefore consists of: 1 center  $\times$  8 directions + 4 corners  $\times$  2 directions + 4 margins  $\times$  4 directions = 32 basic gestures. A dual-line consists in producing two connected line segments. When repeated, a dual-line push is expanded into a **polyline push** (which consists of 32 basic gestures). When expanded into any curve, analytical or statistical, a polyline reaches **curve push** at the limit of  $n$ . A polyline push is produced when the user wants a symbol made up of line segments, like a square, rectangle, or lozenge. A curve push corresponds to any other letter, digit, or punctuation character, whose drawing follows a curve. Finally, the **rotate push** involves two regions, identified by one point or several points, serve as a pivot point and angle with respect to this center. This rotate push can be produced around the center, close to any of the four corners or on the four edges, giving (1 center + 4 corners + 4 margins)  $\times$  2 directions = 18 basic gestures. In total for 2D, we therefore have  $32+32+32+18=118$  basic gestures  $\times$  3 variations (i.e., front, back, or dual-side) = 342 gestures.

**3.2.4 3D Gestures.** In this dimension, the squeeze gestures are now open to produce any motion of the squeezable object in space (Fig. 4). Any object motion in space can be characterized in general by three axis movements called, respectively, *pitch* (rotation around the  $X$  axis, yaw (rotation around the  $Y$  axis) and roll (rotation around the  $Z$  axis). Any such rotation can be initiated similarly around the 6 usual variations (3 faces and 2 directions). **Fold gestures** consists in applying pressure (push) and/or depressure (pull) to fold any part of the squeezable object: one center behaves like a pressure point to fold the neighborhood, four corners (to flip the corresponding part), four margins (to fold a lateral part of the cushion), and two medians along which the folding is operated (horizontally or vertically). Hence, folding gathers 11 basic gestures. We have 3 motion gestures  $\times$  6 variations + 1 center  $\times$  3 variations (3 faces) +  $10 \times 6$  variations =  $18+3+60 = 81$  individual gestures.

The taxonomy of squeeze gestures faces the so-called *curse of dimensionality* [25]: the more capable the squeezable object is, the higher the dimensionality of sensors which leads to a huge taxonomy. The volume of this taxonomy increases so largely that the design space of gestures actually used in this taxonomy generates a sparse space. The ratio between actually used gestures and possible gestures can be very low, almost close to zero.

## 4 EXPERIMENT

We conducted a GES following the classical methodology from the literature [51, 56, 77, 85, 86] to collect users' preferences for squeeze gesture input.

### 4.1 Participants

To recruit participants suitable for our IoT context of use with TV and related devices, we performed a stratification of the population according to age groups based on the percentage of share of total adult TV audience (Source: <http://www.marketingcharts.com>, Simmons Research LLC National Consumer Studies). Six strata were defined (Table 1). A random sampling was applied for each strata to select the corresponding participants from a list of candidates. Thirty-two ( $N=32$ ) participants (18 female, 14 male, and 0 identified as gender variant/non-conforming), aged between 18 and 80 years old ( $M=47.63$ ,  $SD=16.88$ ,  $MD=46.50$  years), contributed to our study. Participant occupations included various domains of human activity (management, social sciences, engineering, computer science, education, law, office and finance administration). Their device usages were distributed as follows on a 7-point Likert scale (1=strongly disagree to 7=strongly agree): computer ( $M=6.34$ ,  $SD=1.13$ ), smartphone ( $M=5.53$ ,  $SD=1.89$ ), tablet ( $M=3.41$ ,  $SD=1.89$ ), game console ( $M=1.69$ ,  $SD=1.40$ ), and Microsoft Kinect ( $M=1.44$ ,  $SD=1.09$ ). No one has ever used a squeezable device before. The majority of participants (22/32=68.7%) was right-handed. No one was ambidextrous. All participants owned smartphones and were used to touch and gesture input.

**Table 1.** Population stratification in age groups.

| Age (years) | Perc. (%) | Female | Male | Total |
|-------------|-----------|--------|------|-------|
| 18-24       | 8.9       | 2      | 1    | 3     |
| 25-34       | 15.4      | 3      | 2    | 5     |
| 35-44       | 16.5      | 3      | 2    | 5     |
| 45-54       | 18.3      | 3      | 3    | 6     |
| 55-64       | 18.7      | 3      | 3    | 6     |
| 65+         | 22.2      | 4      | 3    | 7     |
| All         | 100       | 18     | 14   | 32    |

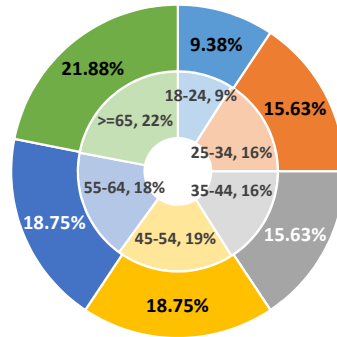


**Fig. 7.** Age groups: sampling vs. population.

### 4.2 Apparatus

We relied on the Squeezee technology [18, 42, 70] to create a squeezable cushion (Fig. 3a). Squeezees are filled with conductive padding (Fig. 2a) and an electronic circuit (Fig. 2b) between 8 electrodes so that  $\frac{n(n-1)}{2} = 28$  unique pairs of electrodes can be scanned. Two multiplexers, one for each electrode of the pair, are used to select an electrode pair. The multiplexers are driven by the digital outputs of an *Arduino Uno Rev 3* board. A voltage divider and the microcontroller's A/D converter are used to measure the resistance between the two selected electrodes.

We selected the interactive cushion as a squeezable object for the following reasons: its geometry benefits from 4 symmetry axes, its volume is simple, its weight is very light thus making it very manoeuvrable, its availability is ubiquitous and its setup or maintenance is straightforward. People are expected to feel familiar with such an object as opposed to a new digital one. In addition, it was expected that they would feel comfortable using a large, soft object like a cushion, a pillow that does not look like an electronic device which may refrain them from producing gestures freely.

Furthermore, a cushion was used successfully in two contexts of use: (1) as a mediator for remote communication scenarios [48] with eight well-recognized gestures (*i.e.*, Hit, Hug, Pat, Rock, Shake, Stroke, Toss, and None) and (2) as a controller of a smart home [64] with thirteen gestures (*i.e.*, push center, push right, push left, push top, push bottom, long push center, slide right, slide left, slide down, slide up, tap with both hands, push right side, turn over and extend with both arms and raise). Fruchard *et al.* [17] did not find any evidence that soft is better or worse for force input than rigid, thus suggesting that we can focus on the context of use or on user preferences without worrying about the material. Finally, a rectangular cushion offers a reasonably good distribution of pressure. A better artifact for pressure distribution would be a circular cushion, but this shape does not benefit from having corners, which are known as recognizable and reachable locations.

### 4.3 Task

Participants were presented with the cushion and given time to familiarize themselves with the new technology. Then, they were presented with *referents*, *i.e.*, functions to control in a home environment, described next in this section, for which they proposed suitable gestures to execute those referents, *i.e.*, gestures that fit referents well, are easy to produce and remember. We did not constrain participants' choices of gestures to any particular context of use or to any hardware ability, as such an influence would have inconveniently narrowed the findings of this study. The experimenter clarified all participants' questions before the study, *e.g.*, with regard to the type of gestures (all types were allowed) or the impossibility to assign a given gesture to more than one referent. Referents were presented randomly per participant. When a referent belonged to a pair of symmetric actions, say "Turn TV on", the next referent presented was always its symmetrical, *i.e.*, "Turn TV off". This allowed participants to propose symmetrical gestures for symmetrical referents if they wished, without having to remember for too long which gesture was assigned to the previous referent. The participants operated with the belief that any gesture they performed was recognizable.<sup>1</sup> Participants' fine motor skills and levels of creativity of the participants were evaluated before the experiment [29], and a short questionnaire was administered after the experiment.

### 4.4 Design

Our study was within subjects with two independent variables:

- (1) REFERENT, nominal variable with 21 conditions, representing common tasks to execute in a home environment in which a Skweezee cushion is available: (1/2) turn the TV on/off, (3) start player, (4) turn the volume up and (5) down, (6) go to the next and (7) previous item in a list, (8/9) turn AC on/off, (10/11) turn lights on/off, (12) brighten and (13) dim lights, (14/15) turn heat on/off, (16/17) turn alarm on/off, (18) answer and (19) end phone call, mute (20) and unmute (21).

<sup>1</sup>This approach enabled participants to invent gestures beyond the hardware and recognition software abilities of the squeezable cushion, which represents a useful result that can potentially inform new technology design for squeezable objects.

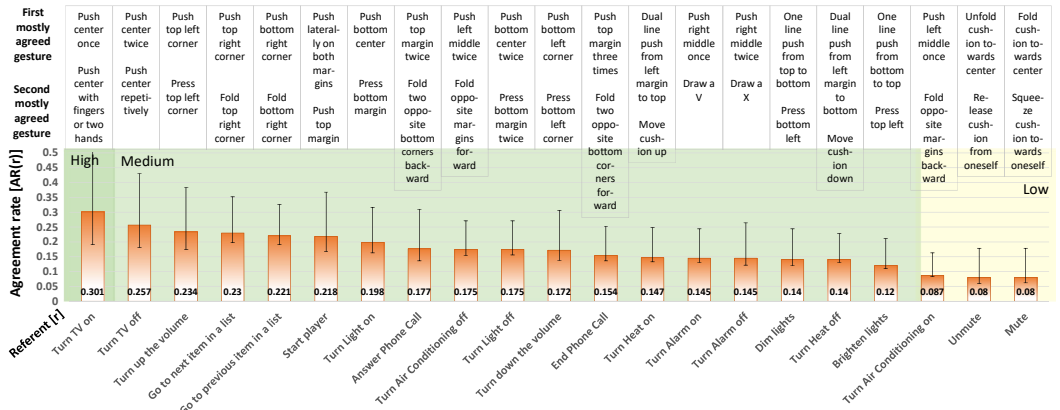


**Fig. 8.** Distribution of squeeze gestures by agreement rate. Note: referents are ordered on the horizontal axis in descending order of their agreement rates ; error bars show 95% confidence intervals computed with the AGATe tool [77] ; top part lists the two most agreed upon gestures for each referent.

- (2) **DIMENSIONALITY**, ordinal variable with four conditions, ranging from 0 to 1, corresponding to the various dimensions of gestures identified in the taxonomy (Fig. 4).

Our choice of referents was inspired by other GES [19, 35, 72, 79] that examined generic tasks for smart homes. Also, most of the tasks are mutually exclusive (e.g., turn on/off the TV) and, according to the context, they can be executed with the same gesture command, e.g., if the TV is on, performing the gesture will turn it off and vice versa. We adopted this design approach to reduce the number of gesture commands that users would need to learn and recall. Moreover, previous studies reported user preferences to employ the same gesture type to perform “on/off” tasks, such as turn on/off devices or pop up/hide menus [72, 79]. We only added the two last referents to the classical list of IoT referents.

## 4.5 Results and Discussion

This section reports and discusses the GES result first according to factors that are usually found in the literature (i.e., agreement rates, actions, and locale) and, after that, according to new factors that are specific to squeeze gestures (i.e., dimension and mechanoreceptor).

**4.5.1 Agreement Rates of Squeeze Gestures.** Fig. 8 depicts the distribution of squeeze gestures in decreasing order of their agreement rate computed with the AGATe tool [77]. Overall, agreement rates obtained for the 21 referents ( $M=0.17$ ,  $SD=0.06$ ) range from  $AR(mute)=0.08$  to  $AR(Turn TV on)=0.301$  and are distributed into three levels: 3 referents received a low agreement (yellow region in Fig. 8), 17 referents received a medium agreement (light green region in Fig. 8), and only one referent received a high agreement:  $AR(Turn TV on)=0.301$ . With regard to the referents having obtained the highest agreement rates, we observed a conflict between two representational symbolisms: Pulvers’ symbolism of handwriting and the physical metaphor. Pulver’s symbolism of handwriting [52] hypothesizes that a handwriting slanted to the right denotes a personality oriented towards the future, while a handwriting slanted to the left denotes a personality oriented to the past. Based on this representation, some participants proposed right-oriented gestures for “Go to the next item in a list” referent, e.g., push/press/fold the top right corner, and left-oriented gestures for “Go to previous item in a list” referent, e.g., push/press/fold the top left corner of the cushion. This representation conflicts with the physical representation that “increase” is at the top and “decrease” is at the bottom. Based on this representation, some participants proposed top-based gestures for increasing

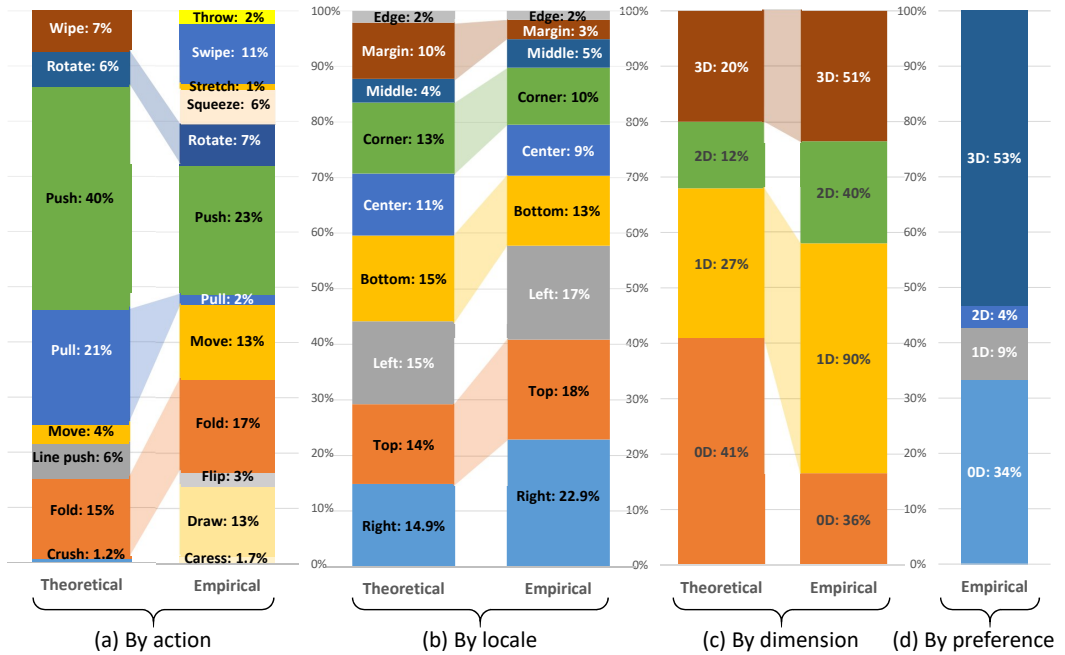


**Fig. 9.** Distribution of squeeze gestures (theoretical vs. empirical): (a) by action, (b) by locale, (c) by dimension, and (d) by preference (empirical only).

(e.g., push top right corner for “Turn up the volume” and push top margin for “Brighten lights”) and bottom-based gestures for decreasing (e.g., Press bottom right corner for “Turn down the volume” and push bottom margin for “Dim lights”). Since Pulver’s symbolism was applied to only one pair of referents, i.e., “Previous/Next” vs. three times for the physical representation, we consistently adopted this representation, which is reflected in Fig. 8, for the mostly agreed upon gesture for each referent. The most challenging question was related to the locale: to which region of the cushion should we assign pairs of related gestures? Based on agreement rates (some of them were quite close for the two fist ones), the pair of volume referents (“Turn up the volume” and “Turn down the volume”) was located in the two left corners and the pair of go-to referents (“Go to previous” and “Go to next”) was located in the two right corners, as this physical representation mimics the layout of these buttons on a remote control, as one participant suggested. The central region was reserved for turning on/off the television and less reachable regions were devoted to less frequent referents: the pair of alarm referents was located to the right margin, the pair of AC referents was located to the left margin. In a singular way, the gestures resulting from GES for muting and unmuting the volume were very squeezing: the gesture “Fold the cushion toward oneself” was preferred because it conveys the idea of “closing” something for oneself, while “Fold the cushion backward” was preferred for unmuting because it conveys the idea of “opening” something with respect to oneself.

**4.5.2 Squeeze Gestures by Action.** Fig. 9-a compares the distribution of squeeze gestures according to the action they involve in the taxonomy (theoretical) vs. those proposed in the GES (empirical). Actions are sorted in alphabetical order with their respective frequency. Not surprisingly, the two most frequent empirically-derived actions more or less match the theoretically-determined ones with comparable frequencies: push gestures (23% vs. 40%), fold gestures (17% vs. 15%). Pull gestures are largely neglected (21% down to only 4%, thus suggesting that participants did not appreciate

pulling) in favor of others (e.g., move gestures increased from 4% to 13%). Wipe gestures were not elicited as opposed to other elicited gestures which were not identified in the taxonomy, thus suggesting that a GES always brings some new insights: caress gestures (elicited, but impossible to recognize), draw gestures (mainly symbols such as a circle, a square, or a rectangle), squeeze gestures as a combination of push and pull, stretch gestures, and throwing gestures in space.

**4.5.3 Squeeze Gestures by Locale.** Fig. 9-b compares the distribution of squeeze gestures according to their locale in the taxonomy (theoretical) vs. those proposed in the GES (empirical). The regions are sorted in decreasing order of their respective frequency. The preferred regions found in the GES largely correspond to the theoretically determined regions in the taxonomy, with only a slight difference in percentage. Probably because the participants were right-handed and read from left to right, the right (23% vs. 15% in the taxonomy) and top (18% vs. 14% in the taxonomy) regions are most often mobilized, followed by their symmetric counterpart: left (17% vs. 15% in the taxonomy) and bottom (13% vs. 15% in the taxonomy). The center was often elicited as a starting point or for pushing, but it remains still marginal (9% vs. 11% in the taxonomy). Although the four corners (10% vs. 13% in the taxonomy) were expected to remain easily accessible, they did not receive much attention. The three regions which are then the least appreciated are the middle (4% vs. 5% in the taxonomy), the margins (3% vs. 10% in the taxonomy), and the edges (2% for both conditions).

**4.5.4 Squeeze Gestures by Dimension.** Fig. 9-c compares the distribution of squeeze gestures according to the number of dimensions they manipulate in the taxonomy (theoretical) vs. those in the GES (empirical). While 0D gestures (e.g., push a certain point) remained predominant in both situations (41% in the taxonomy vs. 36% in the GES), participants largely approved the use of 3D gestures, much more than in the taxonomy (51% vs. 20%) to the detriment of other dimensions: 1D gestures were not appreciated (27% to 9%) and 2D gestures (12% down to only 4%). These results suggest that spatial gestures and the simplest gestures possible were the most popular among participants. This is confirmed by the goodness-of-fit (Fig. 9-d): 3D gestures were preferred in 53% of cases, followed by 0D gestures (34%), by 1D gestures (9%) and 2D gestures (4%).

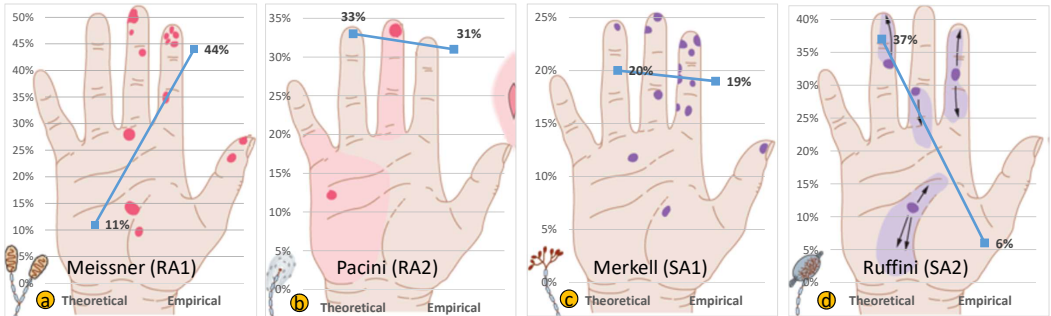


Fig. 10. Distribution of squeeze gestures by mechanoreceptor (theoretical vs. empirical).

**4.5.5 Squeeze Gestures by Mechanoreceptor.** To better understand the squeezing behavior of our gestures, it is important to refer to how our hands are sensitive to pressure. Our human skin is innervated by thirteen types of sensory afferents [27], among which four mechanoreceptive afferent types are responsive to skin deformation. These four different types of mechanoreceptors (a sensory receptor that responds to mechanical pressure or distortion) have varying physiological qualities and can be classified based on their response time to stimuli and receptive field surface. Two mechanoreceptors innervate the epidermis densely, either slowly adapting (Merkell cells,

acronymified as SA1) or rapidly adapting (Meissner corpuscles, RA1) and two that are sparser and end in the deeper tissues and slowly adapting (Pacini corpuscles-RA2) or rapidly adapting (Ruffini complexes-SA2). We classified and compared the 82 gesture classes of the taxonomy (Figs. 5 and 6) and the 26 gesture classes resulting from the GES according to the mechanoreceptors in the glabrous skin of the hand.

Fig. 10 depicts the distribution of gesture classes in terms of percentage with respect to the total number of classes: participants produced a larger proportion (44% in the GES vs. 11% in the taxonomy) of squeeze gestures requiring fine-grained pressure proportion. Pacini and Merkel mechanoreceptors slightly decreased in the GES with respect to the taxonomy: from 33% to 31% for Pacini and from 20% to 19% for Merkel, thereby suggesting that the taxonomy pretty much reflected these gestures depending on their pressure mechanoreceptors. However, the participants produced a much smaller proportion (9% in the GES vs. 37% in the taxonomy) of squeeze gestures that require free and fast-adapting Pacini receptors, suggesting that they do not like to produce gestures with high pressure on large zones. One potential way to improve edge gestures is by tailoring recognition systems to focus on Merkel cells, which respond to edges and small sharp borders by their physiological properties. Finally, microgestures are better captured by fast adapting Pacinian mechanoreceptors, whereas course gestures (e.g., Braille) are captured by fast-adapting Meissner's receptors and slowly-adapting Merkel's receptors. Skin stretch is better captured by slowly-adapting Ruffini endings. We observe that the adaptation speeds of mechanoreceptors increase with the gesture dimensionality: the more the dimension of a gesture increases, the more the physical sensation of the device must be updated quickly by adapting the mechanoreceptor.

## 5 IMPLICATIONS FOR DESIGN

This section discusses the findings and observations of the experiment to derive implications for the design of squeeze gestures in interface design by ranging from the most specific to the more general: starting with the most specific case, that of the cushion, then moving on to general squeeze gestures, and ending with some methodological implications.

### 5.1 Design of Squeeze Gestures for the Cushion

To adequately map gestures elicited for the cushion to their IoT actions, we considered the following criteria in order: gestures with the highest agreement rate (Fig. 8) with the potential importance or frequency of their action, gestures preferred by locale applied on the cushion (Fig. 11, left), gestures by dimension, and symmetrical gestures. Fig. 11, right, shows the main mappings of these gestures to actions located on the cushion.

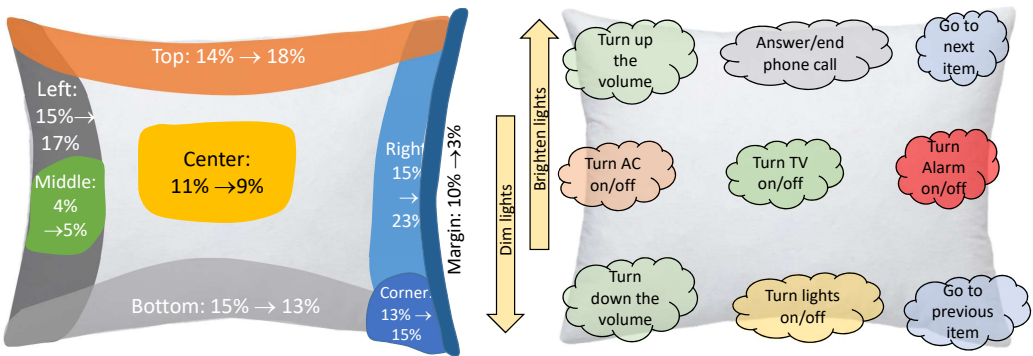


**Fig. 11.** Distribution of squeeze gestures by locale (theoretical → empirical) and their position on the cushion (left). Mapping of squeeze gestures to the actions of the cushion (right).



**Fig. 12.** Push gestures proposed by participants.

“Push center once” ( $AR=0.301$ , high agreement [78]) and “Push center twice” ( $AR=0.257$ , medium agreement) are assigned to the actions “Turn TV on” and “Turn TV off”, respectively, since they benefit from the highest agreement rates, although the center (9%) received less attention than other regions (Fig. 11, left). The participants repeated the same gesture “Push center” to turn the TV on and off, as the cushion did not convey any feedback indicating the TV status.

“Push top left corner” ( $AR=0.234$ , medium agreement) and “Push bottom left corner” ( $AR=0.172$ , medium agreement) are mapped to “Turn the volume up” and “Turn the volume down”, respectively, since the left part received a good attention (17% in Fig. 9, left). The participants preferred to distinguish the two symmetric actions with two different gestures to repeatedly push these regions. In this case, a discrete gesture with repetition was proposed for a continuous action. The participants relied on the left region (17% in Fig. 9-b) since most of them, being right-handed, used their dominant right hand for the most frequent action, *i.e.*, changing channels with “Go to next” and “Go to previous”, which were assigned to the right region (22.9%).

“Push top margin twice” ( $AR=0.177$ ) and “Push top margin three times” ( $AR=0.154$ ) are mapped to “Answer phone call” and “End phone call”, respectively, on the top region (18% of cases). “Push left middle once” ( $AR=0.08$ , low agreement) and “Push middle twice” ( $AR=0.177$ , medium agreement) are mapped to “Turn AC on” and “Turn AC off”, respectively. The low agreement rate obtained for these referents is partially explained by the fact that the participants were not at all used to operate an air conditioning system, which is not the case for other familiar devices.

“One line push left margin to bottom” ( $AR=0.14$ ) and “One line push left margin to top” ( $AR=0.12$ ) are assigned to “Dim lights” and “Brighten lights”, respectively. Pulver’s symbolism is applied: a gesture going down represents a decrease while a gesture going up symbolizes an increase.

“Push” and “Fold” were the first, respectively the second, most agreed upon gestures on the right corner for the “Go to next item” and “Go to previous item” referents, respectively. Their agreement rates are so close that this seems to argue for an equivalence between the two types of gestures. By consistency with the previous gestures, we preferred to map “Push top right corner” ( $AR=0.23$ ) and “Push bottom right corner” ( $AR=0.22$ ) to “Go to next item” and “Go to previous item”, respectively.

The repetition pattern “a gesture once=on, a gesture twice=off”, initiated for television, also appeared for two other pairs: (1) “Push right middle once” ( $AR=0.145$ ) and “Push right middle twice” are mapped to “Turn alarm on” and “Turn alarm off”, respectively; and (2) “Push bottom center once” ( $AR=0.198$ ) and “Push bottom center twice” ( $AR=0.175$ ) are mapped to “Turn light on”, “off”.

Other gestures are also selected, but not represented in Fig. 11, right. “Push laterally on both margins” ( $AR=0.28$ ) is assigned to “Start player”. A “Dual line push from left margin to top” ( $AR=0.147$ ), to “bottom” ( $AR=0.14$ ), is assigned to “Turn heating system on” and “off”, respectively. The second gesture that most agreed for this pair of referents was “Move the cushion up and down”, but less preferred since 3D movements were less preferred than 1D movements. “Unfold towards its center” ( $AR=0.08$ ) suits the “Unmute” referent, conveying the metaphor of closing/opening.

## 5.2 Design of Squeeze Gestures in General

The interactive cushion represents a simple, large, flat and soft object that is easy to deform. Although other deformable objects might be more complex than this cushion, we still observed some implications for squeeze gestures in general.

*Prefer “Push” & “Fold” gestures to “Draw” & “Swipe”.* Among all gestures proposed by participants, “Push” (23% in Fig. 9-a) and “Fold” (17%) were the two most frequent gesture classes, followed by “Draw” (13%) and “Swipe” (11%). “Fold” gestures belong to 3D, the most preferred dimension (53% in Fig. 9-d) and “Push” gestures belong to OD, the second most preferred dimension (34%). On the contrary, “Draw” and “Swipe” belong to 2D (4%) and 1D (9%), respectively. For the last two gestures, pressure applied on the deformable surface may become too gentle to correctly complete the gesture. Applying some pressure to some particular point or area seems easier than maintaining this pressure along a line (1D) or a symbol (2D). Based on the taxonomy, Fig. 12 and Fig. 13 depict the “Push”, the “Fold” gestures, respectively, kept for future use. Both figures are structured according to their locale. Fig. 12 is also structured according to the number of points used for pressure: from 1 point in the center to  $n$  points in the extremities.

*Save the “Move” and “Squeeze” gestures for special cases.* “Move” (13% in Fig. 9-a) and “Squeeze” (6%) are the two remaining classes of gestures still benefiting from an admissible representativeness. Pinching is promising [59], but only slightly emerges in our study in the “Press” gesture, perhaps because pushing (one orientation) is easier than pinching (two orientations). However, moving the cushion always requires some pinching to hold the cushion safely before moving it, as in the “Move the horizontal cushion up and down”. “Press” gestures often come in the second most agreed gesture in Fig. 8, after a “Push” gesture. Note that repetition only occurred for low dimension gestures and rhythm never really occurred.

*Enable “Push” and “Fold” gestures only at some distance.* These gestures are easier to perform when the deformable object is not too close, which may prevent the end user from correctly adjusting the push gesture. Meissner corpuscles are the most involved mechanoreceptors (44% in Fig. 10) since they are responsible for fast-adapting, dense squeezing, thus making them important for “Push”



**Fig. 13.** Fold gestures proposed by participants.

gestures. Pacinian corpuscles (31%) coming second are slower to adapt, but are appropriate for large surfaces. In contrast, Ruffini mechanoreceptors (9%) were not appreciated, probably because fast adaptation to large surfaces is not needed. Vertical folding, such in “Fold left margin” and “Fold right margin” (Fig. 13) seems to be easier than horizontal from a physical viewpoint: the vertical folding axis does not require any hand rotation and adjustment. Users generally like folding the corners as a gesture [82].

*Prefer egocentric gestures to eccentric folding gestures.* Folding movements toward oneself are the most appreciated, not by egocentrism, but simply by physical ease: abduction is preferred to adduction because it does not require extension of movement. Therefore, forward gestures are preferred to backward gestures. In the uni-manual case, fold gestures are preferred when issued forward on the cushion (Fig. 13) and, in general. In the bi-manual case, folding the two lateral margins forward (Fig. 14-b) is also preferred to backward (Fig. 14-a), namely because it does not require lifting the objects and provided that there is enough space. This does not happen with an object having enough space around it: for example, the Nabaztag [13] enables the end user to perform gestures on its ears forward and backward, since there is enough space. Fold, rotate, and flip gestures are representative examples. The “Pull” gestures introduce an exception to this consideration: they are egocentric, but very difficult to realize, therefore very little mobilized in the study as per a drop out from 21% to 2% of gestures (Fig. 9-a).

*Determine the intensity of a “Push” gesture by its number of fingers.* The more fingers are used to issue a “Push” gesture, the more intensity the end user wants to convey. A small and gentle push is

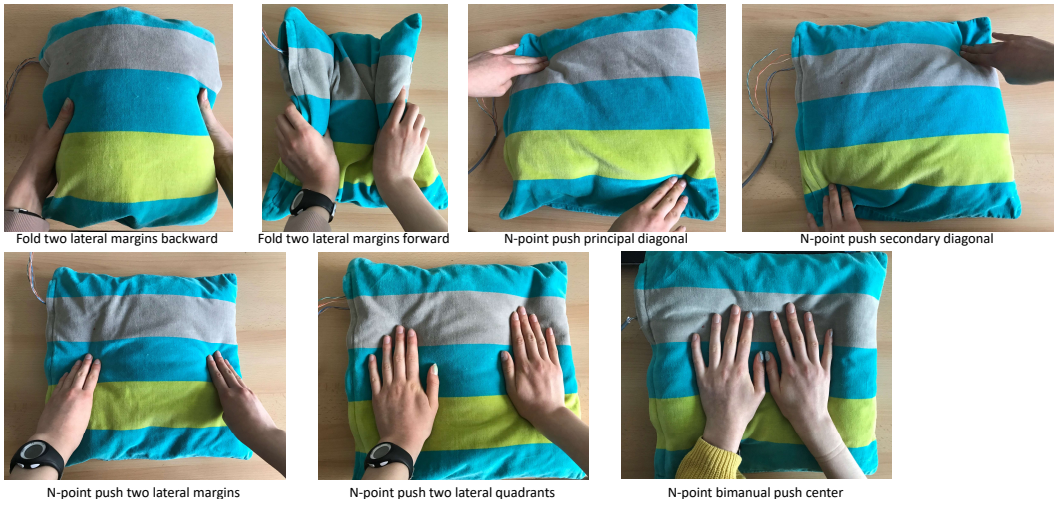


Fig. 14. Bimanual gestures proposed by participants.

often manifested by a single finger pushing the deformable surface, while a medium and a hard “Push” are conveyed by up to 4 fingers and 5 fingers, respectively. A small push confirms an action while a hard push rejects or cancels an action because it expresses disagreement or discontent.

*Limit bimanual gestures to symmetric instances.* Fig. 14 reproduces the bimanual gestures that were the mostly agreed upon participants beyond “Squeeze” (6% in Fig. 9-a) and “Stretch” (1%, a very difficult gesture). The situation is very similar to the unimanual gestures “Push” and “Fold”, except that they are all symmetric. Bimanual “Push” gestures were applied mainly horizontally on lateral margins, quadrants (closer to the center), and in the center, but never vertically, since this gesture requires precise adjustment and potential hand overlap. For these reasons, some participants proposed pushing either on the main diagonal or on the secondary diagonal of the cushion (Fig. 14, top right) according to an imaginary diagonal axis. Bimanual folding was only restricted to lateral margins, either backward or forward (Fig. 14, top left).

### 5.3 Methodological Implications

*Use a taxonomy for both elicitation and identification studies.* The primary use of taxonomy is not immediate for the participants of a study, but rather for its experimenters. Indeed, exploring, defining, and classifying logical gestures first helps experimenters to develop a deeper knowledge of possible gestures in order to better index them. Therefore, participants do not use them unless they are participating in an identification study [1] rather than an elicitation study. In this method, which is the opposite of elicitation, participants must match previously defined gestures (e.g., following an elicitation) with actions materialized by the referents or not. This is similar to a stimulus-response matching test. In this case, it is important to rely on a rigorous classification that remains consistent from one participant to another. For example, when the experimenter collects proposed gestures and writes them down on a gesture sheet, a consistent terminology should be used to avoid mismatching and to check that experimental constraints are met (e.g., checking that a proposed gesture falls in scope, verifying that a gesture is not proposed more than once). In all cases, identification as well as elicitation, the path of the taxonomy allows one to imagine what the dimensionality of the design space is well before conducting the experiment, and then to identify

which fraction of this design space is concerned by the study, often a small part. Therefore, it is not necessary to consider in the final design space all the gestures coming from the taxonomy.

*Rely on the taxonomy for classification and recognition.* Classifying the gestures proposed by the participants is an elusive problem. When this classification is performed manually without any guidelines, different classifications could emerge that impact the agreement rate [19]. When this classification is performed automatically [75], each gesture is then consistently assigned to one and only one gesture class, but the classification could appear difficult. Starting from the taxonomy may help explore various degrees of clustering. For example, Fig. 12 could result into a clustering in terms of number of points ( $n$ -point push gestures should be differentiated from 1-point gestures or not), in terms of corners and margins (since corners are more accessible, margins could be left out or not). Knowing in advance the taxonomy of gestures to be recognized could also help in the supervision of machine learning algorithms to accurately classify gestures.

*Submit related referents randomly and sequentially.* Overall, referents were randomized per participant. When a referent that has a symmetric referent was selected, such as for “on/off”, “increase/decrease”, “forward/backward” examples, the related referent should be presented in sequence so that the participant could propose gestures that are also related and correspond to the actual symmetry or relatedness of the referents. Otherwise, there is a significant risk to see gestures proposed for related referents being totally independent, without exploiting their relatedness.

## 6 LIMITATIONS OF THIS WORK AND THREATS TO VALIDITY

While the initial research question was to identify similarities and differences between theoretically defined and empirically derived squeeze gestures, the study conducted in this paper contributed to eliciting research by analyzing only the user’s preferred gestures corresponding to control of the intelligent home component through a soft cushion and the hand motion. This specific artifact introduced a restriction to the research question located at four levels:

- (1) At the level of the artifact: although an interactive cushion represents an artifact with several advantages [48, 64], it only represents a single category in the “Non-rigid HCI” framework, thereby leaving other categories untouched. Squeezing a large, soft, regular, symmetrical cushion cannot be compared to squeezing a small, hard, possibly irregular and asymmetrical object, or a flexible object like the Ninja Track toy [28]. Therefore, different shapes, sizes, weights, rigidities, textures, and positions of the artefact were not considered.
- (2) At the level of the referent set: referents used in this study (Section 4.4) cover discrete actions (e.g., on/off) and linear actions (e.g., increase/decrease), but not genuine 2D or 3D actions.
- (3) At the level of uncovered squeeze gestures: it is not because a theoretical analysis with the help of a taxonomy and an empirical analysis by elicitation have been carried out that we have been able to discover the complete set of gestures, but probably a large part of them.
- (4) At the level of the method used, the replicability of the method followed and/or the conduct of another method could allow the discovery of other gestures resulting in another taxonomy and another distribution, impacting the approval rate.

Threats to validity could affect the design and conduct of the experiment. According to Wohlin’s classification [88] and to a survey of such threats in empirical software engineering research [14], we clustered these threats into four types:

- *Internal validity*: it deals with influences that affect the factor concerning causality. The experiment can suffer from: *Experience of the participants*, which means that the experience of the participants is not sufficient to conduct the experiment. Our participants had no prior experience with the interactive cushion. To mitigate their lack of experience, we relied on the

familiarity of the artefact. *History*, which means that differences arise when treatments are applied at different times. To avoid this threat, we conducted the experiment in one continuous session per participant. *Instrumentation*, which means that the changes in the instrument, experimenters, or scorers could affect the results. All the referents were presented and used consistently and randomly from one participant to another. *Interactions with selection*, which means that when there are different groups of participants, different behaviors with the cushion could appear. To minimize this threat, we uniformly used the same instruments to all participants of the experiment. They belong to one of the partitioned population strata. Covering all elicitation with a reasonable number of participants is impossible to achieve. Another threat that appears is *Ecological validity* [32], which means that the context in which the experiment was conducted affects the results. To minimize this threat, participants conducted the experiment in a controlled environment, *i.e.*, a quiet office room.

- *External validity*: this type of threat concerns conditions that limit our ability to generalize the results of our experiment to a real practice. The experiment could suffer the following threats of this type: *Interaction of selection and treatment*, which means the effect of having our population sampling being not representative enough of the population we want to address. In our experiment, we cannot ensure that the results can be generalized to participants with different experience from our sample. They had a rather minimal experience in using IoT technology, which could benefit differently than for experienced people, who might be more used with IoT. Another threat that appears is *Interaction of settings and treatment*, which means the effect of not having the experimental setting or material representative of real practice. To minimize this threat, we ensured that the room mimicked, but did not reproduce, a typical home environment.
- *Construct validity*: this type of threat concerns generalizing the design implications to a theory of squeeze gesture behind the experiment. The experiment could suffer the following threats of this type: *Evaluation apprehension*, which means that some people are afraid of being evaluated. To minimize this threat, we communicate to participants that the experiment was aimed at improving as much as possible the features of the cushion to optimize their user experience, without mentioning the term “experiment” or “test”. Another threat is *Hypothesis guessing*, which means that when people participate in an experiment, they may find out what the purpose and the intended results of the experiment are. To minimize this threat, we did not talk about our research question nor mention the expected gestures.
- *Conclusion validity*: this type of threat deals with the ability to draw the correct conclusion about relations between the treatment and the outcome. The experiment could suffer the following threats of this type: *Fishing*, which means that the experimenter is looking for a specific result. To minimize this threat, we did not provide participants with any guidance beyond the declarative instructions. Another threat that appears is *Reliability of measures*, which means that the measures (*e.g.*, the agreement rate [77, 78]) used in our analysis could include errors. To minimize this threat, all the measures are applied by one experimenter and verified by another researcher. Another threat is *Random heterogeneity of participants*, which means that when there is heterogeneity in a study group, there is a risk that the variation due to individual differences is larger than due to the treatment. To minimize this threat, we recruited participants according to a stratified sampling and we used demographic questionnaires to detect differences among the participants’ profiles.

Finally, there are related questions raised by this study but left untouched.

*No consideration for gesture recognition.* We did not address the problem of squeeze gesture recognition, although we could. Nunez *et al.* [48] recognize eight haptic gestures with more

than 80% precision between participants on an interactive cushion by combining the cushion's deformation data with motion data. The recognizer is orientation-invariant. Suzuki *et al.* [64] achieved the recognition of 13 gestures with 82.3% of accuracy, but it had to be placed on a surface with a fixed orientation, thus being orientation-variant. As long as squeeze gestures can be modeled as time-ordered series of points in 2D or 3D [73], any state-of-the-art gesture recognition algorithm (see [38] for a survey), including the recognizers of the "\$-family," such as \$1 [87], \$N [4], \$P [76], ProTractor [37], or \$3 [34], could be employed to classify these gestures. However, these gesture recognizers have never been tested for squeeze gesture recognition although they could. For example, JackKnife [67] is a modality-agnostic gesture recognizer and, as such, could be directly used for squeeze gesture recognition. Instead, machine learning (ML) techniques have been employed, mainly Support Vector Machines (SVM) and Hidden Markov Models (HMMs) [70].

*No gesture feedback.* We did not provide participants with any feedback about their proposed gestures to preserve the quality of the experiment. For example, ShadowGuides [15] provides on-demand assistance to the user by combining visualizations of the user's current hand posture as interpreted by the system (feedback) and available postures and completion paths necessary to finish the gesture (feedforward).

*Need for learning the gesture set.* The gestures from the elicitation study are recognized to be more easily memorized [45], but still need to be globally evaluated once they are incorporated into a real system. For example, learning the set of gestures resulting from the study requires an investment of time from new users and some method can facilitate this process [7].

## 7 CONCLUSION AND FUTURE WORK

This paper compared theoretically-defined squeeze gestures determined by a systematic analysis of gestures based on their dimension and empirically-derived, user-defined gestures resulting from a gesture elicitation study by focusing on a particular squeezable object: a deformable cushion based on the Skweeze environment [70]. On the one hand, 82 gesture classes were defined in the taxonomy and 26 gesture classes were identified in the study. The analysis of the user-defined squeeze gestures lead us to come up with gestures for 21 actions in a way that materializes a physical representation of commands and a mapping of squeeze gestures to designated locales of the cushion. While the agreement rates were computed and discussed for user-defined gestures only, we were able to compare both sets of gesture classes according to classical factors (*i.e.*, action, locale) and according to two newly introduced factors (*i.e.*, dimension to characterize the preferred dimensions expressed by participants and the mechanoreceptors, a significant factor when pressures comes into play from the human point of view).

In this paper, we conducted the classical methodology for a gesture elicitation study. We would like to further investigate in a future experiment whether participants would propose the same or different squeeze gestures in a *referent-less approach* compared to this *referent-based approach*, as devised in this paper. To this end, an informal inquiry could completely relax the elicitation by simply asking each participant to freely suggest 10 squeeze gestures without any task, referent, or measure in mind. This represents an open question that is aimed at imposing no constraint on the process and checking the taxonomy with elicited gestures only. Then a directed interview could partially relax the elicitation by asking each participant to suggest 3 squeeze gestures per gesture dimensionality (*i.e.*, 0D...3D) and a task they would carry out for this gesture. This represents a mixed question (and not a totally closed question) since it involves the dimensionality as a suggestion and feeding the set with elicited gestures and referents provided by participants themselves, as opposed to presenting referents by ourselves.

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