Grasping Microgestures: Eliciting Single-hand Microgestures for Handheld Objects

Adwait Sharma
Saarland University
Saarland Informatics Campus
Saarbrücken, Germany
sharma@cs.uni-saarland.de

Joan Sol Roo
Saarland University
Saarland Informatics Campus
Saarbrücken, Germany
roo@cs.uni-saarland.de

Jürgen Steimle
Saarland University
Saarland Informatics Campus
Saarbrücken, Germany
steimle@cs.uni-saarland.de

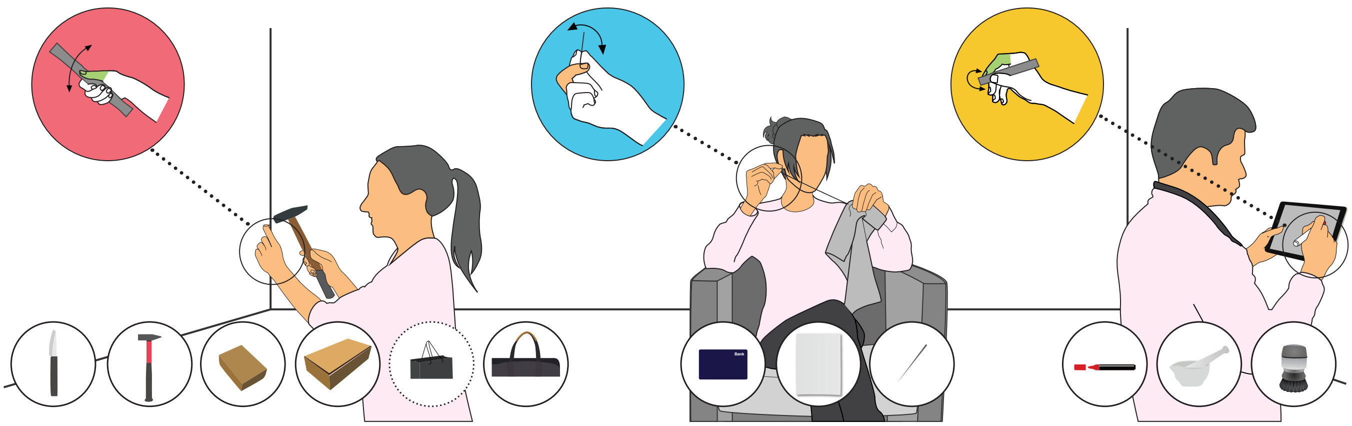

Figure 1: Grasping Microgestures enable direct and subtle interactions with computer systems while holding an everyday object. This paper presents empirical results from an elicitation study with varied objects, investigating the effect of grasp and object size on user's choice of microgestures, preferred locations, and fingers used.

ABSTRACT

Single-hand microgestures have been recognized for their potential to support direct and subtle interactions. While pioneering work has investigated sensing techniques and presented first sets of intuitive gestures, we still lack a systematic understanding of the complex relationship between microgestures and various types of grasps. This paper presents results from a user elicitation study of microgestures that are performed while the user is holding an object. We present an analysis of over 2,400 microgestures performed by 20 participants, using six different types of grasp and a total of 12 representative handheld objects of varied geometries and size. We expand the existing elicitation method by proposing statistical clustering on the elicited gestures. We contribute detailed results on how grasps and object geometries affect single-hand microgestures, preferred locations, and fingers used. We also present consolidated gesture sets for different grasps and object size. From our findings, we derive recommendations for the design of microgestures compatible with a large variety of handheld objects.

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CCS CONCEPTS

• **Human-centered computing → User studies**; **Interaction techniques**.

KEYWORDS

Gestures; microgestures; gesture recognition; touch; grasp; object; elicitation study

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1 INTRODUCTION

Gestural user interfaces for computing devices most commonly require the user to have at least one hand free for interacting with the device, to be able to move a mouse, touch a screen or perform mid-air gestures. In contrast, it remains difficult to interact with computing devices when both of the user's hands are occupied holding everyday objects. These situations arise in many contexts, for instance while working with tools in the kitchen, workshop, or office, or while carrying bags for shopping or traveling.

Advances in miniaturized, embedded or wearable sensors now open up opportunities for new forms of gestural input with busy hands: subtle and rapid microgestures [3] performed using a single hand. These one-handed microgestures can be performed along with a primary task with a handheld object, as they require only subtle finger movements and interrupt the primary task only for a few seconds. We envision such gestures to be useful for controlling computing devices while using conventional, passive handheld objects. Some example use cases are shown in Figure 1: for instance, the resulting gestures could be used to access a user manual while holding workshop tools, to control a video tutorial about sewing while holding a needle, or to intuitively switch between drawing tools while holding a pencil. We also believe these microgestures offer powerful means for interacting with new types of ubiquitous computing devices.

Microgestures have already proven to be useful for direct and subtle interaction with ubiquitous computing systems [8, 20, 27]. Prior work has systematically investigated single-hand microgestures in a hands-free context [7]. It is to be expected, however, that hands-free microgestures are considerably different from gestures that can be performed when hands are busy. The number of fingers needed for holding or manipulating the handheld object largely constrains the set of possible microgestures. Comparably little prior work has investigated this setting. Pioneering work by Wolf et al. [50] has contributed an early investigation with 3 objects, while other work has investigated gestures on self-sustained objects, such as the steering wheel [2]. However, we still lack a systematic investigation of a more comprehensive set of object geometries and their respective grasps to investigate the complex relationship between handheld objects and microgestures. It remains an open question as to what are appropriate interactions from an end user's perspective when hands are busy holding an object.

In this paper, we present results from an empirical user study with 20 participants that elicited microgestures while the hand is holding an object. We call those "grasping microgestures". It is the first such study that systematically compares a large set of grasps and handheld objects of various geometries and size. Using a taxonomy of six different grasps and two object sizes, we selected 12 representative handheld objects from various domains. Our study employed the user elicitation method introduced by Wobbrock et al. [48]. The analysis of over 2,400 user-generated microgestures for 10 referents on all objects allowed us to identify user agreement, user's mental models and gesture preferences. Our key finding is to answer how grasps and object geometries affect the design space of microgestures performed on handheld objects in the light of the interactional constraints caused by holding a physical object in one's hand. We characterize users' preferred types of action when hands are busy and show that these actions mainly depend on the referent, rather than on the grasp or object. In contrast, the choice of fingers and action location is strongly influenced by the grasp and the size of the handheld object.

We add to the existing elicitation method by proposing *statistical clustering* of users' elicited gestures. This approach facilitates finding previously undiscovered patterns through a full data-driven interpretation. It identified similarities of among different geometries and ultimately allowed us to present three main cluster sets of gestures that cover interactions for all 12 varied objects.

We further derive design implications that guide designers of microinteractions in choosing microgestures compatible for use with handheld objects. Subsequently, we identify recommendations for the design of future sensors and gesture recognition systems. We believe our results are an important step toward enabling gestural interfaces that are compatible with varied settings when the user's hands are busy.

2 RELATED WORK

Our study is informed by prior empirical elicitation studies, conceptualizations of grasping, and advances in sensing techniques for microgestures:

Elicitation Studies of Gestural Interaction

Previous work has identified the importance of including end-users in the gesture design process [31, 32, 34, 48, 49]. It has been shown that gestures defined by larger groups are easy to remember, since they are conceptually simple and less demanding. The method of eliciting gestures from end-users, initially proposed by Wobbrock et al. [49], has quickly found widespread use in various areas, ranging from tabletop gestures [49] to drones [12]. More closely related to our work are elicitation studies of microgestures and gestures performed with handheld objects. A recent study by Chan et. al [7] investigated properties of single-hand microgestures, including actions and fingers used, but in an empty-hands setting without objects. Several studies have investigated gestures on self-sustained objects, such as steering wheels and bike handles [2, 11, 44]. Our work is different in that users had to continuously hold the handheld objects.

Little previous work has empirically investigated input while the user's hands are busy. Lee et al. [23] explored deformation-based user gestures on various materials such as plastic, paper, and elastic cloth. We followed a similar approach using real-world objects. In our work, we leverage the gripping posture and embrace the challenge of using only one hand. We took inspiration from previous work by Wolf et al. [50], who investigated micro-interactions to support secondary tasks while the user's primary task involves holding an object. This work investigates three objects: steering wheel, cash card and stylus. Gestures are identified based on consultation with four experts. We extend this work by investigating a wider variety of 12 objects, conceptually based on a taxonomy of grasps. Based on a large set of gestures elicited from end-users we contribute the first empirical analysis of how grasps and object size affect the properties of microgestures.

Taxonomies of Grasping

The rich variety of possible actions that can be performed by the hands has been conceptualized in different domains, including in medical, robotics, and bio-mechanical fields. Taxonomies of discrete grasp have been proposed for various goals [5, 9, 19, 25, 33]. Schlesinger [39] put forth a classic taxonomy initially developed for designing prosthetic hands. A comprehensive survey of grasp taxonomies can be found in [28].

Sensing Hand Gestures

In recent years, considerable advances have been made in sensing input performed with hand and finger gestures. Various sensing approaches have been presented for detecting hand gestures. Camera-based approaches [4, 8, 14, 20, 27, 29, 43, 51], electromyography-based approaches [37, 38] and bioacoustic approaches [1, 10, 14, 21, 52] have demonstrated the recognition of one-hand gestures. Passive techniques are also proposed [22]. Another highly accurate motion-tracking approach detects microgestures based on millimeter-wave radar [24]. Furthermore, researchers have demonstrated sensing by instrumenting the skin itself [18, 35, 46]. As an alternative to augmenting the user's body, sensors can be integrated into the object [40, 41, 53]. Recently, [15] has suggested creative alternatives for no-handed interactions with smartwatches. Although research on sensing of interaction while hands are holding objects is still in an early stage, one of our aims with this study is to provide guidance on future research in sensing.

3 METHOD

To investigate how users perform microgestures while they are holding objects using various grasps, we conducted an elicitation study.

Participants

20 healthy participants (10m, 10f, mean 26.2y; median 25y; 2 left handed) were recruited from different professional backgrounds (arts, engineering, law, psychology) and various cultural backgrounds (Western Europe, Middle East, India, China, USA). Participation was voluntary. Each participant received a compensation of 20 Euros.

Apparatus

Following the method proposed by Wobbrock et al. [49], we intentionally refrained from using any sensing technology so as not to bias the user's response by restrictions imposed by equipping everyday objects with sensors. Participants used passive handheld objects. No additional feedback was provided. The entire session was video recorded.

Referents

Our list of referents is informed by [7, 49]. In total, we selected 10 referents that comprise discrete (*select*, *delete*), binary (*accept*/*reject*, *next*/*previous*) and continuous (*increase*, *decrease*, *move*, *rotate*) commands. We kept the set of referents compact, first because microinteractions are commonly used for a small set of simple and quick commands that do not disrupt a primary activity, and second to keep the study feasible despite the number of conditions, which was considerably larger than in typical elicitation studies from prior work.

Grasps

We based our grasp conditions on Schlesinger's seminal classification of six prehensile postures that account for variations in object shape, hand surfaces and hand shape [28, 39]. This classic taxonomy is frequently used in prior work [13, 16, 17, 36, 38, 42]. The grasp conditions are:

- *Cylindrical*: for holding cylindrical objects, such as a coffee mug.
- *Palmar*: for grasping with palm facing the object, such as grasping a book.
- *Hook*: for grasping a heavy load such as a bag.
- *Lateral*: for grasping flat objects such as paper.
- *Tip*: for grasping small objects such as a pen.
- *Spherical*: for holding spherical objects such as a ball.

Object Size

We hypothesized that within each grasp type, the size and weight of the object would affect the grasp and hence the set of microgestures that can be performed. We performed a pilot study with two interaction designers who were asked to perform any microgestures they could think of on objects of largely differing weight (ranging from a feather-weight styrofoam ball to a 10 kg dumbbell) and largely differing size

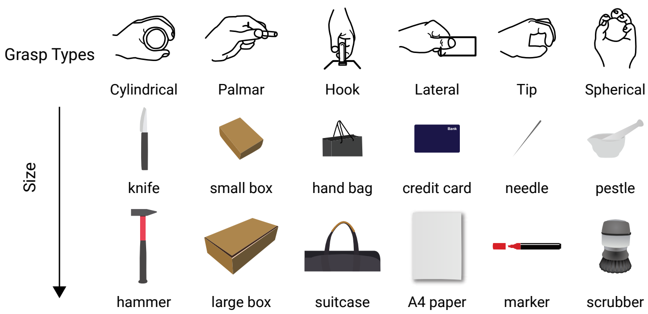

Figure 2: Selected grasps and corresponding objects for small and large object sizes.

(ranging from tiny needle to a 75 cm yoga ball). The results of this pilot study indicated that size has a strong effect on microgestures. To give only one example, while holding a cylindrical object of small diameter, the user can perform actions such as snapping around the object or touching his fingertips. These are not possible with larger diameters. We found that weight has a much less strong influence on the microgestures that can be performed, as long as the weight allows a user to comfortably hold the object using a single hand. For example, one can tap the same way on a very heavy ball and on a lighter ball.

We therefore decided to investigate variations of object size only and selected a small and a large object for each grasp.

Representative Handheld Objects

We chose a total of 12 handheld objects that represented our 6 grasp conditions as well as a significant variation in size within each grasp. The set of objects is shown in Fig. 2. To identify representative objects that cover varied environments, two interaction designers have iteratively compiled a list of objects, selecting objects from the literature [26, 50] and adding further ones from everyday usage. We opted for real-world objects instead of abstract geometrical props to make it easier for participants to conceive gestures they would make in a realistic setting. Our final set of objects contains: *knife* and *hammer* for cylindrical graps; *small cardboard box* and *large cardboard box* for palmar grasp; *bags with small and large handle* for hook grasp; *credit card* and *A4-size paper sheet* for lateral grasp; *sewing needle* and *marker* for tip grasp; *pestle* and *scrubber* for spherical grasp.

Task and Procedure

We used a within-subject design. The order of referents, grasps and object sizes was randomized. Participants elicited gestures while standing. First, we chose one of the 12 objects (in random order). The participant was given the object that represents the grasp and object size condition of this trial and was asked to naturally hold it steadily in the dominant hand. For each object, we then presented all 10 referents one after another, in a random order. For each referent, the participant had to make a microgesture using the same hand that was holding the object. To reduce legacy bias, we applied *priming* [30] by informing participants about the potential of such 'Grasping Microgestures'. In addition, we ensured today's computing technology was neither used nor visible during the study: names of objects and referents were presented on paper slips, and we asked participants to place their personal devices out of sight.

In a few cases, the participants chose a different grasp than the one to be tested in the trial. Then the experimenter asked the participant to present a second gesture using the correct grasp. We also asked for a second alternative if the proposed gesture involved rotation or movement of the object. This was taking into account that in some real-world environments it would not be possible to move or rotate the object (e.g., a glass full of water or a power tool).

For each participant, the experiment took approx. 3 hours and was conducted in two sessions of 1.5 hours each.

Analysis

Overall, we elicited 10 (referents) x 6 (grasps) x 2 (object sizes) x 20 (participants) = 2,400 microgestures. An additional 131 microgestures were performed in case of change in grasps, object movement or rotation, as described above. This gave a total of 2,531 gestures. We used descriptive labeling, chunking, and phrasing [6] for our data analysis. We analysed more than 50 hours of video recording and manually annotated each proposed gesture with its properties: which type of action was performed (e.g., tapping, sliding, pressing), direction (if applicable), count (e.g., 2 for double-tap), finger(s) used (including phalanges of the fingers and the thenar and hypothenar eminences), location type (on object, on body, or in air), location on object faces (similar to [2]). The labels for action type and location type were iteratively refined using an open coding approach.

4 RESULTS

In this section, we present results of the elicitation study. We analyze agreement between participants and analyze the properties of the proposed microgestures, including action types, location of interaction and finger usage. The results show that microgestures strongly depend on the type of grasp and the size of the handheld object, as these offer different affordances and constraints. We are able to show that all 12 object conditions can be clustered into four types, for each of which we present a consolidated consensus gesture set.

REFERENT	OBJECTS													
	cylindrical		palmar		hook		lateral		tip		spherical			
	small	large	small	large	small	large	small	large	small	large	small	large	MEAN	STDEV
select	0.300	0.321	0.300	0.342	0.276	0.242	0.314	0.321	0.321	0.405	0.219	0.347	0.31	0.05
accept	0.195	0.143	0.224	0.142	0.174	0.205	0.152	0.147	0.174	0.113	0.105	0.194	0.16	0.04
reject	0.137	0.138	0.065	0.065	0.147	0.148	0.147	0.258	0.347	0.119	0.087	0.152	0.15	0.08
delete	0.072	0.110	0.090	0.065	0.071	0.049	0.087	0.083	0.073	0.083	0.082	0.057	0.08	0.02
next	0.179	0.105	0.168	0.132	0.084	0.189	0.147	0.086	0.142	0.105	0.110	0.081	0.13	0.04
previous	0.174	0.137	0.158	0.174	0.100	0.200	0.116	0.069	0.162	0.074	0.132	0.071	0.13	0.04
increase	0.586	0.637	0.432	0.568	0.186	0.290	0.257	0.242	0.248	0.437	0.479	0.374	0.39	0.15
decrease	0.732	0.563	0.390	0.584	0.179	0.333	0.363	0.247	0.300	0.426	0.437	0.374	0.41	0.15
move	0.323	0.602	0.589	0.814	0.652	0.478	0.320	0.648	0.317	0.524	0.468	0.344	0.51	0.16
rotate	0.514	0.652	0.814	1.000	0.510	0.729	0.484	0.447	0.308	0.431	0.241	0.308	0.54	0.23
MEAN	0.32	0.34	0.32	0.39	0.24	0.29	0.24	0.25	0.24	0.27	0.24	0.23		
STDEV	0.22	0.24	0.24	0.33	0.19	0.19	0.13	0.18	0.09	0.19	0.16	0.13		

Figure 3: Agreement rates for all referents, shown individually for grasps and object sizes.

Agreement Rate

To identify the level of consensus between participants' proposals, we calculated agreement rate between participants using the AGreement Analysis Toolkit (AGATe) and the modified agreement rate introduced by Vatavu *et al.* [45]:

$$AR(r) = \frac{|P|}{|P|-1} \sum_{P_i \subseteq P} \left(\frac{|P_i|}{|P|} \right)^2 - \frac{1}{|P|-1} \qquad (1)$$

We considered participants to be in agreement if they proposed a gesture of the same action type and the same properties, for instance same direction of swiping or same number of taps. This resulted in 18 unique gestures. Agreement rates were calculated individually for each grasp and object size.

The results are shown in Figure 3. Agreement rates ranged from 0.049 (low agreement, AR $\leq$ 0.1) to 1.000 (very high agreement, AR > 0.5). The mean AR across all objects and referents was 0.281 (SD = 0.19), which can be qualified as medium agreement (0.1 < AR < 0.3). This range of agreement is comparable with those reported in prior work involving hands as a primary input [7, 23, 47].

Agreement rate among different referents. We observed considerable variation in agreement rates for different referents, as commonly reported in prior work. Participants appeared to agree more for commonly used operations like Select. This can be explained not only by a stronger legacy bias, but also by the relative ease of finding a simple mapping for referents such as tapping for select. We also observed higher consensus for commands related to physical actions (Move, Rotate), for which most participants proposed gestures that involve directional movement. In contrast, we observed lower agreement rates for critical commands such as Delete and Reject. Many participants intended to avoid false activation of such critical operations and hence tried to make unique suggestions.

Agreement rate among different grasp types. Our results reveal that agreement rates vary among different grasp types. Palmar and Cylindrical grasps show higher agreement than the remaining grasps. This finding might be related to the constraints imposed by these grasps, which restricted finger movement more considerably than in other grasps. Object size had a less considerable influence on agreement rates.

Action Types

To understand what actions the proposed microgestures contain and how the choice of action depends on the referent and on the handheld object, we identified action types and their distribution for referents and objects.

The results are depicted in Figure 4(top). They show that the type of action chosen strongly depends on the referent. We identified the following action types:

(1) *Tap* (26.1% of all proposed gestures): Participants chose tapping actions most frequently for 3 of the 10 referents (Select, Accept, Delete). For Select, 79.3% of all proposals involved tapping. During the think-aloud session, users mentioned its ease and resemblance to input on touch devices. Participants also leveraged the spatial precision of choosing one specific location of tapping in a some proposals for Accept, Reject, and Delete, as well as for Next and Previous.

(2) *Press* (8.2%): Press was among the least performed actions. Some participants intentionally used pressing, as opposed to tapping, as a means to confirm for Select, Accept, and Delete.

(3) *Stretch* (9.2%): Some proposals included in-air finger movement, such as pointing with a finger, or stretching out one or multiple fingers. For Reject and for Delete 16 participants proposed stretching out two or three fingers (middle, ring and pinky), as if to flick something away.

(4) *Swipe* (37.7%): Continuous actions such as Increase-Decrease and Next-Previous leveraged the fluid, directional as well as continuous nature of swipes. Although

all referents were shown in random order, and hence dichotomous pairs of referents were not necessarily presented one after another, participants intentionally made use of opposite direction movements for such dichotomous pairs *("outward as increase, towards myself is decrease" [P10])*. Participants also acknowledged that object geometry plays an important role in helping map directions.

(5) *Draw* (16.4%): We classified all non-linear swipes as Draw. Participants used this action in more than 80% of the proposed gestures for Move and Rotate, leveraging intuitive spatial mappings. For instance, a circular sliding motion was used for rotate, while directional movements similar to input on a trackpad were used for Move. 6% of the proposed gestures for Delete were a 'cross' symbol.

In addition to these types of action, a very small number of proposals involved changing the grasp (0.9%), moving the object (0.5%), or rotating the object (0.8%). As these were very rarely proposed and would not be compatible with all objects, we do not recommend using those.

Contrary to distribution across referents, grasp and object size did not considerably affect the choice of action type, as shown in Figure 4 (bottom). A few minor exceptions are notable, however. Spherical grasp with large object (Scrubber) showed the highest percentage of draw actions, which represented almost one in three proposed gestures of this condition. We observed that the thumb movement is restricted, however, the index finger can move easily over the large surface and draw gestures, similar to the posture of holding a computer mouse. In-air gestures were performed mainly with grasps on objects where some of the users' fingers were not involved in holding the object and hence free to be moved in mid-air. This is visible in case of lateral grasp (13.1% and 16.1%) and tip grasp with the small sewing needle (17.8%).

These findings confirm empirical findings of prior work that investigated designers' rather than users' mental model. They also extend to a larger set of grasps and objects and for the first time quantify distributions.

Overall, we can conclude that the choice of action type is mainly guided by the referent, rather than the grasp or object.

A second central implication of our findings is that the vast majority of proposed gestures uses tapping, swiping or drawing, which are all established multi-touch interactions common on handheld devices. Taken together, these findings suggest there might be a possibility of defining consistent microgestures for handheld objects that use similar actions for all objects while being compatible with a user's established mental model of multi-touch interaction.

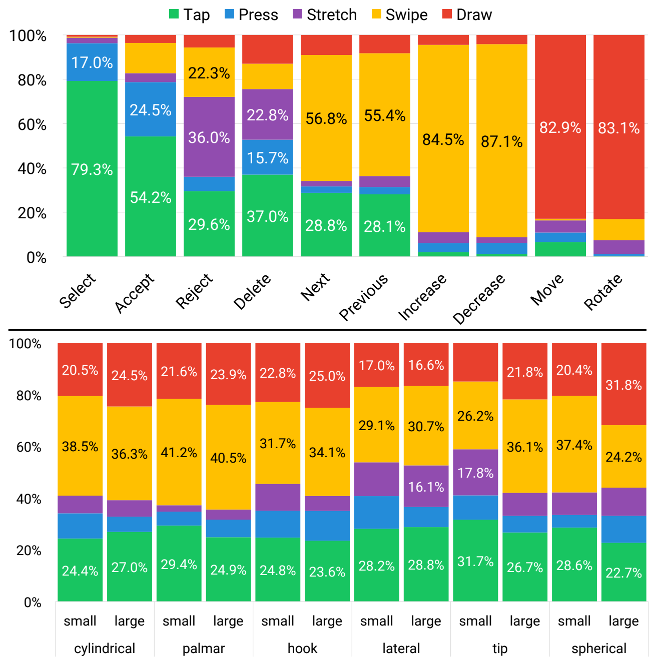

Figure 4: Action distribution for Referents (top) and Objects (bottom).

Action Location: On-Object, On-Body, In-Air

While action type appears mostly unaffected by grasps and objects, our results show that the handheld object strongly influences the location *where* this action is performed. As we did not put any restrictions on where participants did microgestures with their dominant hand, participants were free to perform those not only on the handheld object itself, but also on their own hand or fingers, or in mid-air.

As shown in Figure 5, the location used for interaction depends on the size of the object. This plot arranges objects based on the proportion of microgestures that were done *on* the object, rather than on the body or in air. (Note that in all these cases the participant kept holding the object.) It becomes apparent that with increasing size of the object, a higher proportion of gestures are on the object. On the box objects, around 90% of all gestures have been performed on the object itself. Some users commented that making gestures on the large box is similar to using a touchpad. On the contrary, as small objects do not offer large surface real-estate for performing gestures, a considerably higher fraction of gestures was performed on the user's own hand or fingers, or in mid-air in case of small objects. The most extreme case, the needle, offers virtually no space for gestures, hence almost 90% of all gestures have been made on the body or in mid-air.

44.0% of the gestures performed using the needle were mid-air gestures due to the lack of surface area on the object. Very few people used their index finger as a pointer. In case

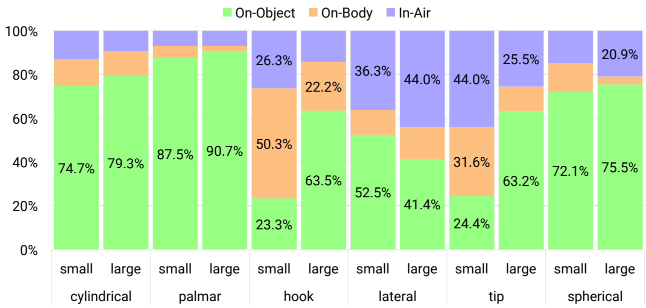

Figure 5: Action location for each object.

of the needle, and also for paper, a common strategy consisted of making touch gestures with a finger on the palm of the *same* hand, like on a touchpad. Some participants were amused once they found out that they can actually touch their palm with the same hand's finger. Once they discovered this affordance, they started leveraging the considerable space for gesturing provided by the thenar region while holding small objects. 12.1% of all proposed gestures for paper and 11.0% for needle used this strategy.

In contrast to self-sustained objects, such as the steering wheel [2], the hand could not be easily moved on our handheld objects to reach distant locations without risking the object falling down. Hence, the majority of microgestures appear close to the position where the object is held. Furthermore, none of our participants used prominent visual landmarks on the object (like a printed logo) for interaction.

Use of Fingers

While prior work on free-hand microgestures has identified frequency rates of finger use [7], we are not aware of any such information reported about microgestures with handheld objects. Taking into account that grasping an object constrains finger movement, it is to be expected that different grasps considerably affect which fingers are used for microgestures. Here, we contribute the first frequency usage for each finger based on different grasps and object size.

The results are depicted in Figure 6. They empirically confirm that the grasp considerably affects the choice of fingers for microgestures. We identified two main clusters, based on grasps: For Hook grasp, Palmar grasp, Cylindrical grasp and Spherical grasp, the vast majority of gestures were performed using the thumb or index finger. These grasp types have in common the use of most or all fingers for holding the object. This allows the user to temporarily move the thumb or index finger, while using the remaining fingers to stabilize the hold.

By contrast, for Lateral grasp and for Tip grasp with a small object (sewing needle), the vast majority of gestures were performed using middle, ring or pinky finger, or a combination of those. These grasps have in common holding the object with both thumb and index finger. As their movement was constrained, participants resorted to using the remaining fingers for microgestures. In those cases, the middle finger was most frequently used. For instance, a user might be comfortable using the middle finger to perform a swipe on a digital pen to increase the stroke width. In contrast, using the thumb would create an imbalance in the grip and might lead to dropping the object. However, there were some instances where participants avoided using the middle finger due to social inappropriateness of gesturing with the middle finger, although the gesture would have been easier to perform than with the ring or pinky finger *("[it is] socially unacceptable if I use the middle finger, which is easy to do" [P4])*.

Tip grasp with a larger object (marker) was situated between both clusters, with a fairly even distribution between thumb/index and middle/ring/pinky.

Analyzing the first group in more detail, our data reveal that microgestures in Hook grasp and Cylindrical grasp most frequently use the thumb and rarely use the index finger. Also, Palmar grasp shows a slight preference for the thumb. We believe this is particularly likely because in such cases the object rests against the other fingers and hence the thumb can be easily released from the object for interaction. In contrast, Spherical grasp and Tip grasp (large object) make more equal use of the thumb or index finger.

Similar to the findings by [2], our data show that the choice of finger used to perform the gesture is almost unrelated to the associated command. Contrary to [7], participants did not complain about not remembering the exact finger. Our assumption is that this is because of the additional constraints present in settings with handheld objects: since the grasp posture restricts the choice of fingers to be moved, it helps users to remember the fingers used for the interaction.

Qualitative Analysis

We used an open-coding approach, with iteratively refined codes, to describe the gestures' properties, such as the type of action, gesture location, and finger details. In addition, we annotated gesture properties with unique observations we made during the study and post-session interviews. Altogether, the analysis revealed several interesting insights about how participants performed gestures. For instance, when performing the gesture on a small object, participants showed a variety of techniques to overcome the limited amount of space on the object. This included slightly adjusting the grasp or retracting fingers that were not involved in a gesture to create additional space on the object for making touch gestures. Participants clarified that techniques like unconsciously bending fingers for creating an interaction surface were inconsequential to the core gesture. Similarly,

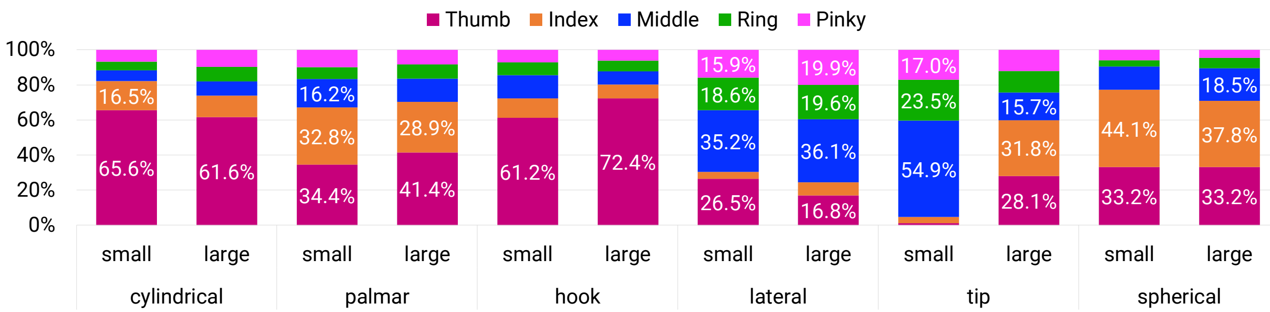

Figure 6: Fingers used as an actor for grasping microgestures.

participants completed linear swipes through diagonal movements when a specific horizontal or vertical movement was not possible on the object geometry (e.g., swiping at the backside of the paper using the middle finger *("I don't have vertical movement... doing it diagonally" [P4]).*

In almost all cases, users performed touch gestures with the center of the fingertip. In some cases, however, like sliding along the pestle, the ulnar (inner) side of the finger was used due to the ease of contact. There were also very few instances where the hand's metacarpus (palm) region was used as an input mainly for Press actions while holding the object. Moreover, participants preferred using the nail instead of fingertips for interactions involving "knocking" on an object. These variations with different finger parts can expand the design space of performing gestures on an object. Several participants commented that they would be willing to repeat the same gesture to allow the system to distinguish the gesture from normal object manipulation and to ensure it is recognized as intended input. While feedback is outside the scope of this study, one participant explicitly stated that he would appreciate getting vibrational feedback as a confirmation the gesture was accepted.

Clustering of Grasps

A major challenge in designing microgestures for use with handheld objects is the large number of grasp types, which is further complicated by additional influencing factors such as object size. As it would not be desirable to design individual gesture sets for each condition, we sought to further extend the information provided by the agreement score analysis. In addition to finding consensus gestures for a given referent, we aimed at analytically identifying commonalities among the users' microgesture proposals in different conditions.

While statistical clustering is a commonly used technique in the fields of machine learning and pattern recognition, to the best of our knowledge we are the first to leverage this data-driven approach in an elicitation study to reveal patterns. We used all gesture properties we had annotated in our dataset, including action location, finger use, etc. To avoid a bias, we removed information about the experimental

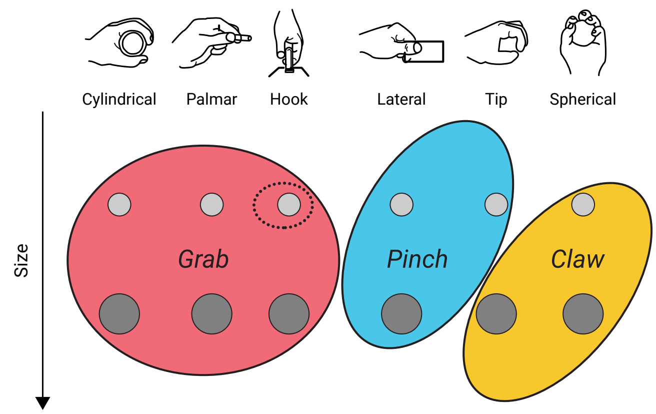

Figure 7: 3 Clusters derived from the commonalities of the interaction amongst all 12 representative objects.

condition (grasp type, object size). We first applied Principal Component Analysis (PCA) for dimensionality reduction of our annotated data. Furthermore, we used the simple yet robust K-nearest neighbor approach for clustering. We employed the elbow method to find the optimal number of clusters (k=5). After analysing the K-nearest output and visualizing the level of separation between clusters, we observed that the frequency distribution of gestures from the same condition across the five clusters showed a significant peak on exactly one cluster for all conditions. Hence, we applied the majority rule to map each condition (grasp x object size) to exactly one cluster. It is worth noting that one of the 5 clusters did not contain any majority vote, and hence became an empty set in our final grouping. The resulting clusters, which we call *Grab-a*, *Grab-b*, *Pinch*, and *Claw* are shown in Figure 7.

Cluster Grab-a comprises grasp types where the user's fingers are reaching around the handheld object, allowing thumb or index finger to be moved, while the object is offering considerable surface real estate for interactions. Cluster Grab-b (shown with dotted lines) can be qualitatively explained by the combination of a handle with small diameter and the Hook grasp. This resulted in a unique affordance allowing the thumb to reach around the handle and perform

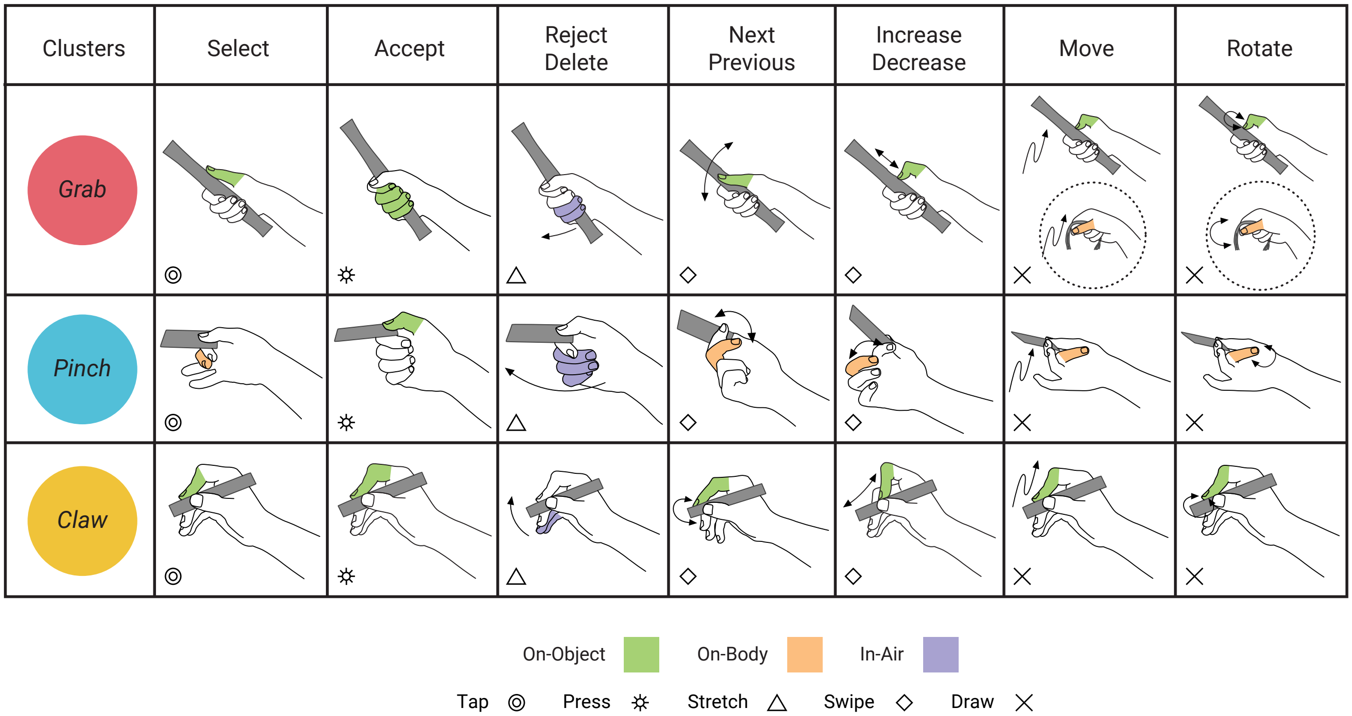

Figure 8: Consensus gesture set for all 3 main clusters.

gestures on the user's hand, specifically at the distal phalanx (front) side of the index finger.

Cluster Pinch comprises grasp types that predominantly make use of the thumb and index finger for holding the object. Cluster Claw comprises grasp types that have predominant use of index finger rather than thumb.

Comparing this empirical clustering with the intuitive, conceptual grouping of grasps done by Saponas et al. [38], it is interesting to note that both approaches resulted in three groups of grasps. Our empirical findings confirm the intuitive grouping of Palmar and Cylindrical grasps. Likewise, our findings confirm that Hook grasp forms its own group, however only for small objects. Most important, our findings show that contrary to the grouping proposed earlier, Spherical grasps systematically differ from Palmar and Cylindrical grasps in the use of index finger vs. thumb, and hence should not be grouped together.

Consensus Gesture Set

We used these three clusters to design consensus gesture sets for microgestures with handheld objects. These are the first end-user driven gesture sets that cover a large range of grasp types and objects.

For each referent, we assigned the most frequently performed gesture, similar to [49]. The gestures for Reject and Delete are grouped together because of a high consensus for this particular action by our participants.

Figure 8 shows the final consensus gesture sets. Drawing from the quantitative data and our observations, we suggest that conventional mapping of Tapping and Swiping offers the most convenient mapping for Select, Increase/Decrease, and Next/Previous actions. The press modality has been most frequently proposed for confirmation. Stretching of fingers, used for Reject and Delete commands, require higher user consciousness, reducing the likelihood of any false input. The circular or directional Draw action defined for Move and Rotate provide natural spatial mappings.

Even though we present three consensus gesture sets–one for each main cluster identified in the previous section–it is to be noted that these gesture sets share many features. For each referent, the action type and main action properties are similar in all gesture sets. The first and second gesture sets only differ in use of thumb vs. index finger. The difference between the second and third gesture set is that gestures appear on-body or in-air vs. on-object.

Despite the large variations in grasps and object sizes these user-defined gestures support, we believe these microgestures will be easy to memorize and easy to perform. This is because they build on established mental models of touch interaction, systematically leverage affordances and constraints offered by grasps, and use similar gestures for all grasp types.

5 IMPLICATIONS FOR DESIGN

Based on the results presented in the previous section and qualitative feedback of participants while thinking aloud and during interviews at the end of each session, we derive several implications for design of systems for gestural input.

Microgestures on Everyday Handheld Objects

A central question that motivated our study was to find out how the multitude of grasps and object geometries affect users' choice of microgestures they perform while holding objects. Would designers of applications for mobile computing and the Internet-of-Things have to design a custom set of specific gestures for each type of object? Are there commonalities that allow us to use the same gestures on many objects? The former would be very undesirable from a usability standpoint and would risk frustrating users up to the point of rejecting the new opportunities unleashed by microgestures. The latter would be highly desirable but seemed unrealistic to us before conducting the study.

One of the primary and surprising findings of our study is that three gesture sets are sufficient to cover all 6 main types of grasp and 12 objects in our study. In addition, the gestures are similar for all three sets, as they use the same action types and gesture properties and mainly differ only in what finger is used for making the gesture and whether the gesture is performed on the object, on body or in air. Given these choices are mainly guided by the affordances offered by the object (small or large surface for performing gestures) and constraints of the grasp posture (which fingers can be moved easily while holding the object), we believe users can easily perform the gesture that is compatible with the given object. Ease-of-learning and memorization is further supported by our finding that most gestures build on established touch gestures commonly known from touchscreens. While this might have been strongly influenced by legacy bias, we believe it is a strength of the gesture set, as it is compatible with established mental models of interaction. Our findings further show that miniature objects as small and thin as a needle can be used as an input medium. Participants performed similar microgestures as on other objects, but with more on-body and in-air interaction. Fairly large objects, such as a large cardboard box or a suitcase, can be used for single-handed microgestures, too.

Avoiding False Positives

False positive input is a challenge while interacting with handheld objects, as hand or finger movements that relate to the primary activity might be incorrectly recognized as an input microgesture. While our study design did not focus on this question, our results indicate a number of strategies that participants have used to avoid false positives. Many participants were particularly inventive for gestures that trigger a critical action like Deletion. The most varied actions have been proposed for these referents to ensure they are different from movements that relate to the primary activity *("Normally wouldn't touch down" [P9])*. For instance, one strategy was to intentionally change the grasp while using the marker, and touching the lowest tip part (area with ink). Another strategy was to stretch only the pinky finger while keeping the middle and ring finger in a flexed position. In contrast, during natural movement, stretching the pinky would normally result in at least some stretching of the ring finger as well. Participants went as far as using double or even triple taps, or intentionally touching the sharp area of the knife, to ensure communication of the input gesture is intended. As an alternative to implementing a specific activation gesture or mapping critical functionality to gestures that are hard to perform, we recommend that designers implement an undo functionality that allows the user to undo any previous action that might have been triggered by a false positive. The Reject gesture from our gesture set could be used for this function.

Sensor Placement

The finger and location information provided in this study can be used to inform sensor placement for gesture recognition systems on the handheld object, on the user's hand and fingers, or even both.

Our results show that by only sensing input from the thumb and the input finger, a large majority of all gestures can be sensed for all grasps other than Lateral and Tip with small object. Gestures in Cylindrical and Hook Grasps can even be reasonably captured with the thumb alone. For the Lateral and Tip (small) grasps, sensing input from the middle finger would offer a minimum instrumentation. While previous studies identified the pinky as the least frequently used finger, we uncovered its unexplored dexterity while holding small objects like needle and credit card.

Participants mentioned the thenar region as a large fleshy area of the palm *("Tap with middle finger on the fleshy part of the palm" [P11])*, similar to the 'touchpad' of laptop and used it extensively as an input surface for touch gestures while holding the needle. Designers of sensing systems should consider capturing input on this area. Only 1 out of 20 participants suggested the use of Shear action, and also Press was rarely proposed. We therefore conclude that in most cases it seems sufficient to capture touch contact alone.

Our location information can also be used to avoid false positives on the object, placing the sensor at a location farther from the place where the object is grasped. Being harder to reach, it is less likely the user would interact on it unintentionally.

6 LIMITATIONS

In our study, we investigated gestures performed within a short pause during the primary activity. As stated by Ashbrook [3], such microinteractions should take less than 4 seconds to initiate and complete to smoothly integrate with the primary activity. For this work, we opted against gestures that would be performed simultaneously, without stopping the primary activity. The effect of many possible physical primary activities are beyond the scope of this study and should be investigated separately in future work.

To help participants invent realistic gestures, we opted for actual objects instead of abstract geometric props. The choice of objects was centered around providing familarity with the object. Some participants even commented that they have never thought that such objects they commonly use can be used for interaction. Using realistic objects for the respective grasps implied that there is some natural variation in size and weight of objects. We acknowledge this could be a limitation from a formal experiment perspective, yet we believe it is outweighed by the benefits of being able to cover diverse realistic objects in this exploratory study. The effects of object size and object should be investigated in more detail in future work.

For the sake of comparability among objects, we have used rigid objects. Future work should study how affordances of soft materials might change user behavior. For instance, users might perform more squeezing or pressing actions with soft objects.

To create a more relaxed and creative atmosphere, the participants in our study were not blindfolded, which we deemed important for inventive gesture proposals. While most of the proposed gestures can certainly be performed during eyes-free interaction, we clarify that this is not necessarily guaranteed, as participants were able to look at the site of interaction.

7 CONCLUSION AND FUTURE WORK

In this paper, we have presented results from the first elicitation study of microgestures with handheld objects that systematically compared the effect of grasps and object sizes on the gestures conceived by end-users. Our findings revealed a strong influence of grasp and object size on usable microgestures. The results of data-driven clustering revealed that the effect of various grasps and object sizes on microgestures can be reduced to only three clusters. Our findings, together with the consolidated gesture sets we have presented, can be used for designing gestural input and gesture recognizers that work in settings where the user's hands are busy with holding an object.

Future work should investigate how gestures should be designed that can be performed simultaneously with a primary object manipulation task, such as hammering or writing. The effect of object weight also remains to be studied in more detail as well as how the choice of gestures depends on the object's material. Another important question for future work is to specifically identify strategies for avoiding false positive input during everyday activities. We see our findings as a first step toward consolidated microgestures that work with all common handheld objects and hope these findings will be useful for designers of both input gestures and gestural recognition systems.

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