iFAD Gestures: Understanding Users' Gesture Input Performance with Index-Finger Augmentation Devices

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ABSTRACT

We examine gestures performed with a class of input devices with distinctive quality properties in the wearables landscape, which we call "index-Finger Augmentation Devices" (iFADs). We introduce a four-level taxonomy to characterize the diversity of iFAD gestures, evaluate iFAD gesture articulation on a dataset of 6,369 gestures collected from 20 participants, and compute recognition accuracy rates. Our findings show that iFAD gestures are fast (1.84s on average), easy to articulate (1.52 average rating on a difficulty scale from 1 to 5), and socially acceptable (81% willingness to use them in public places). We compare iFAD gestures with gestures performed using other devices (styli, touchscreens, game controllers) from several public datasets (39,263 gestures, 277 participants), and report that iFAD gestures are two times faster than whole-body gestures and as fast as stylus and finger strokes performed on touchscreens.

CCS CONCEPTS

• **Human-centered computing** → **Gestural input**; **Ubiquitous and mobile devices**.

KEYWORDS

Index finger, finger augmentation devices, taxonomy, gesture input, gesture analysis, gesture recognition

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1 INTRODUCTION

Gesture input is mainstream on mobile and wearable devices, from smartphones to smartwatches [38,56], smartglasses [24,35], and smart jewellery [30,31,73]. While predominantly available in the form of touch input, other gesture types—free-hand, mid-air, whole-body—are increasingly supported by a variety of devices, e.g., input around smartwatches [38], mid-air gestures with smart rings [31], finger tapping above desktop devices [115], and combined touch and hand poses for tablets [67]. The diversity of these gesture types requires specific sensing technology, such as motion sensors to detect finger [36], hand [67], and device [92] orientation, touch [93] and video sensors [59] for swipes and hand poses, and depth sensors [40,106] to recognize on-body gesture input.

In this large family of gesture-sensing devices, Finger Augmentation Devices (FADs) [95] enable a wide variety of gesture types of the kinds enumerated above for always-available input. Such devices include smart rings [4,31,36], fingernail addenda and displays [22,98,130], and multi-finger devices [15,67,125]; see Shilkrot et al. [95] for a survey. In this landscape, *we argue that devices that instrument the index finger hold a privileged position due to the rich interactions they afford on and with the index finger, yet the corresponding gestures have not been systematically examined so far.* There is multiple evidence in this regard. For instance, the index finger is conveniently located on the hand, easily accessible with the thumb for a variety of touch, tap, swipe, and pinch gestures [66,102,119]. During precision grips, the index finger is the first digit to make contact with the target, while eye gaze is always directed towards the contact point [12]. Also, the index finger is intuitively used for referential pointing as an attention-directing gesture [3] and, while most gestures develop culturally, a fact that has implications for the design of gesture UIs [26,72], pointing with the index finger is the exception [27, p. 480]. Unfortunately, index-Finger Augmentation Devices (iFADs) have not been examined as a distinct type of a device with distinctive characteristics in the wearables landscape, but merely as another member of the FAD family [95]. Similarly, iFAD gestures, of which we demonstrate a large variety with many desirable quality properties for input, have not been systematically investigated, but only considered sporadically when new FADs were introduced [4,9,10,18,21,33,102,130]. In this work, we focus on iFAD gestures and make the following contributions:

(1) We introduce a four-level taxonomy of iFAD gestures that is index-finger-centric, encompassing of a large diversity of gesture types, and technology-agnostic to be used with a variety of iFADs and gesture recognizers. We show how our taxonomy complements existing gesture classifications from the scientific literature, which are either too generic or specialized to capture the nuances and diversity of gestures that can be performed with the index finger.
(2) We conduct a controlled experiment with 40 iFAD gesture types informed by our taxonomy, and analyze 6,369 gestures collected from 20 participants using a low-cost, custom-made iFAD with a 3-axis accelerometer. Our results show that iFAD gestures are *fast, low effort,* and *socially acceptable* in many

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public contexts. We also compare iFAD gestures against gestures collected with other devices, including stylus and finger gestures articulated on touchscreens, motion gestures performed with game controllers, and whole-body gestures.

(3) We compute recognition accuracy rates for iFAD gestures by using popular gesture recognizers, readily implementable on wearable platforms. We report 83.8% accuracy for our whole set of 40 iFAD gestures, 98.7% for a selected subset of 10 gestures, and 97.1% for a mixed subset of 20 iFAD gestures spanning all of the categories of our taxonomy.

Our results show that iFAD gestures have many desirable quality properties for input, while our taxonomy and companion resources constitute practical information for researchers and practitioners interested in wearables that leverage the versatility of gesture input performed with the index finger. To foster more investigations in this direction, we release our dataset (details in Section 8) that, to the best of our knowledge, is the only publicly available data on gestures performed with a finger augmentation device.

2 RELATED WORK

We relate to prior work on gesture input performed with wearables for finger augmentation, such as electronic rings and other FADs, and overview the sensorimotor capabilities of the index finger.

2.1 Gesture Input with FADs

A variety of FADs have been proposed for always-available input; see Rissanen et al.'s [88] overview of ringterfaces, Shilkrot et al.'s [95] survey of FADs, and Vatavu and Bilius' [110] examination of gestures for rings, ring-like, and ring-ready devices. For example, Ashbrook et al. [4] introduced Nenya, a magnetically-tracked ring featuring eyes-free input via twisting and sliding of the ring along the finger to select items from a 1D menu, Stearns et al. [97] developed TouchCam, a FAD with a miniature video camera for on-body input, and fingernail devices [22,98] have been proposed for subtle finger input. However, this prior work has largely focused on the technical novelty of FADs and less on the richness of possible gesture types, which explains the small size of gesture sets implemented for these devices, e.g., two gestures for NailDisplay [98], four spinning and sliding gestures for Nenya [4], four directional gestures for Magic Ring [51] and Thumb-In-Motion [10], eight swipes for Ringteraction [33], five OctaRing multi-finger taps [68], etc. A few exceptions exist, such as Lim et al.'s [67] set of twenty gestures combining touch and finger input and Zhang et al.'s [132] thirteen gestures for ThermalRing. However, one conclusion after surveying the scientific literature on FADs is that a systematic examination of FAD gestures is lacking since most of the effort has been put into prototyping new devices and corresponding gesture recognition techniques. In this context, *index-finger gestures have been considered merely as another category of gestures that can be performed with a FAD, despite their distinctive quality properties for input.* Next, we highlight these properties with the sensorimotor capabilities of the index finger to contextualize our focus on iFADs.

2.2 The Index Finger

In their overview of human hand function, Jones and Lederman [53] presented empirical data for the diverse capabilities of the index finger. For instance, with the exception of the thumb, the index finger has the greatest range of abduction and adduction movements (p. 15) and is the most spatially acute compared to the middle and ring fingers (p. 133); the index finger appears in many prehensile patterns (p. 139); and the thumb and index finger are the most independent digits of the hand (p. 145). Cavina-Pratesi and Hesse [12] found, that when an object is grasped with the precision grip, eye movements tend to fixate close to the contact point of the index finger on the object. Moreover, the extensive contact area between the thumb and the index finger is a unique human characteristic [53, p. 12] compared to nonhuman primates, enabling a variety of gestures and grips. This evolutionary advantage enables not only a diversity of combined finger movements, but also higher information bandwidth, e.g., Balakrishnan and MacKenzie [7] showed that the index and the thumb working together in a pinch grip have higher bandwidth than other segments of the upper limb.

Gestures performed with the index finger are also highly distinctive and easy to perform. Sharma et al. [94] found that single-finger movements are rare in everyday interactions with objects, and proposed SoloFinger, a single-finger input technique that is resilient to false activation of microgestures. Of the SoloFinger gestures, gestures performed with the index finger were rated among the most easy to perform in a user study. Also, in a gesture elicitation study of single-hand microgestures, Chan et al. [13] noted the convenience of using the index finger: "Besides using the index finger for its dexterity or convenience, users frequently referred to the index finger as the pointer finger, which evoked a feeling of confidence or direction" (p. 3411). The dexterity of the index finger, its frequent usage for pointing, prehension, and exploration, and its convenient location next to the thumb make it attractive for input with iFADs and demand a dedicated, systematic scientific examination.

3 A TAXONOMY OF IFAD GESTURES

We are interested in gestures performed with the index finger that can be sensed with iFADs. Various iFAD form factors [95,110] afford different gesture types, e.g., electronic rings afford twisting gestures on the finger [4], but also drawing in mid-air [31]. However, because of the diversity of iFAD gestures and their articulation specificity involving the index finger, it is difficult to characterize them with existing gesture taxonomies [55,74,122], which fail to capture their specific nuances. Thus, we introduce a dedicated taxonomy for iFAD gestures that is (1) centered on the index finger, (2) encompassing of a diversity of gestures fully specified at distinct scales of the human body, from finger-level to whole-body input, and (3) technology-agnostic, so that it can be used with a variety of iFADs and gesture recognizers. We start with a definition of iFAD gestures and an enumeration of their quality properties for input.

3.1 Definition and Qualities of iFAD Gestures

Shilkrot et al. [95] defined FADs as "finger-worn devices with an additional augmentation other than their form, that provide a supplemental capability for one or more fingers using the finger itself as a central element" (p. 30:4). This definition is useful as the starting point for specifying iFAD gestures since it sets the overall conceptual context of devices designed to be worn on fingers. However, Shilkrot et al. did not go into the discussion of specific FADs that afford specific gesture types, e.g., gestures of the index finger, since they were mainly interested in characterizing all possible classes of FADs. Thus, their five-level FAD taxonomy with the *form factor*, *input*, *output*, *intended action*, and *application domain* dimensions is too generic to catch the nuances of iFAD gestures. Based on Shilkrot et al.'s generic specification of what a FAD is, we provide the following operational definition for iFAD gestures:

> ***Definition.*** iFAD gestures are gestures performed with or on the index finger, detectable by a FAD that is worn on the index finger (i.e., an iFAD) with the purpose of providing input to an interactive system.

This definition is encompassing of a variety of gestures of the index finger, as we show in Subsection 3.2, and is agnostic to the iFAD form factor and sensing technology to detect those gestures. Furthermore, the stated scope of iFAD gestures is to provide input to interactive systems, which delimits them from exploratory procedures examined in haptics research [53] or body movements for systems that output gestures [23,78,90]. We complement this definition with four *quality properties* (Q_1 to Q_4) that we identify for iFAD gestures, as follows. We expect gestures performed with the index finger to be familiar to users because of the ubiquity of referential pointing, touch, and pinch grips in everyday life; see Section 2.2. Consequently, iFAD gestures are likely to be *fast* (Q_1), *low effort* (Q_2), and *socially acceptable* (Q_3) in many public contexts. To substantiate Q_1, Q_2, and Q_3, we present in Section 4 an experiment designed to evaluate and understand user performance with and perception of iFAD gestures from the perspective of these three quality properties. Also, gestures performed with the index finger can take a variety of forms, from subtle movements of the finger to drawing in mid-air to gestures performed at the scale of the whole body for body-referenced and on-body input. Thus, iFAD gestures are also *versatile* (Q_4) to be employed in many ways. To structure the spectrum of iFAD gestures in a systematic way and differentiate among various iFAD gesture types, we formalize Q_4 in Subsection 3.2 with a dedicated technology-agnostic taxonomy of gestures performed with and centered on the index finger.

3.2 A Taxonomy of iFAD Gestures

We seek a dedicated taxonomy to structure and specify iFAD gestures that is agnostic to the technology to sense and recognize those gestures and that centers on and highlights the distinctive capabilities of the index finger. Following Subsection 2.2, these capabilities are represented by the dexterous movements of the index finger at the finger scale (e.g., tapping or rubbing against the thumb), its frequent usage during prehension at the level of the hand (e.g., the pinch grasp), and its privileged use for deictics at the scale of the arm to direct attention (e.g., pointing). From this perspective, the integrating dimension of our taxonomy is the *body scale* at which gestures are performed with the index finger in the personal, peripersonal, and extrapersonal space of the user. In deriving the categories of our taxonomy, we start from the smallest scale corresponding to gestures performed at the level of the index finger, e.g., taps on the iFAD [125], and we progressively consider larger scales and gestures enabled by correspondingly larger body parts, i.e., the hand and the arm, up to gestures that are fully specified at the scale of the whole body, such as on-body [79,97], body-referenced [106], and gestures for grasp UIs [124]. By capitalizing on the *body scale at which gestures of the index finger are fully specified,* we introduce a four-level taxonomy (Figure 1) of iFAD gestures, as follows:

❶ **Finger-level iFAD gestures** represent input at the scale of the finger, e.g., tapping and swiping on the iFAD with the thumb [10,33,102] and sliding and twisting the iFAD across the finger [4,39]. We differentiate between *touches* on the iFAD and *grasps* that involve manipulation of the iFAD.

❷ **Hand-level iFAD gestures** represent poses and movements of the index finger that are fully specified at the level of the hand and for which the spatial location of the hand is not relevant. For example, this category includes pinch gestures between the thumb and the index finger and tapping other fingers or the surface of the hand with the index finger [29,99,102], sign language and emblems involving the index finger [14,52], and microgestures [13,94]. We differentiate between *poses* (the pose of the index finger is important, as in the "victory sign" cultural gesture, not the movement of the finger into that pose) and *motion* (the motion of the finger specifies the gesture completely, whereas the finger pose is not important, i.e., a circular movement of the index finger).

❸ **Arm-level iFAD gestures** represent movements of the arm in mid-air to produce stroke gestures with the index finger. Examples include pointing [15,37,47], drawing letters [54,132], and free-hand movement around a device [20,42,130]. The gesture is captured from the vantage point of the index finger, but the arm is required for the underlying movement. We differentiate between *unistrokes* and *multi-strokes* [71].

❹ **Body-level iFAD gestures** represent on-body input and near-the-body, on-surface gestures performed with the index finger. Examples include taps and swipes on the body [76,79,97] and gestures on objects for surface interaction [61,83,94] that can be sensed from the motion and orientation of the index finger. Smart-Pockets [106] and FabriTouch [43] gestures, where the user points to and touches specific parts of their clothes, e.g., the trousers pocket, also fall into this category. At this level, we differentiate between gestures performed in the *personal space*, with reference to the body, and gestures in the *peripersonal space*, near the body.

3.3 Relation to Other Gesture Taxonomies

Our taxonomy encompasses a diversity of iFAD gestures by centering on the index finger and leveraging the body scale at which the index finger specifies the gesture. Next, we show how our taxonomy positions with respect to existing classifications of human gestures from the scientific literature. To this end, we identify three types of classifications according to their scope, purpose, and application domain: (1) taxonomies that specify human hand function in motor control theory, (2) taxonomies of gestures employed for communication, examined in psycholinguistics, and (3) taxonomies of gestures examined in HCI for interactive systems; see Figure 1, right for correspondences.

3.3.1 Motor planning and control. Many classifications of hand gestures have been developed in the motor planning and control literature, see MacKenzie and Iberall [70] for an overview, but the

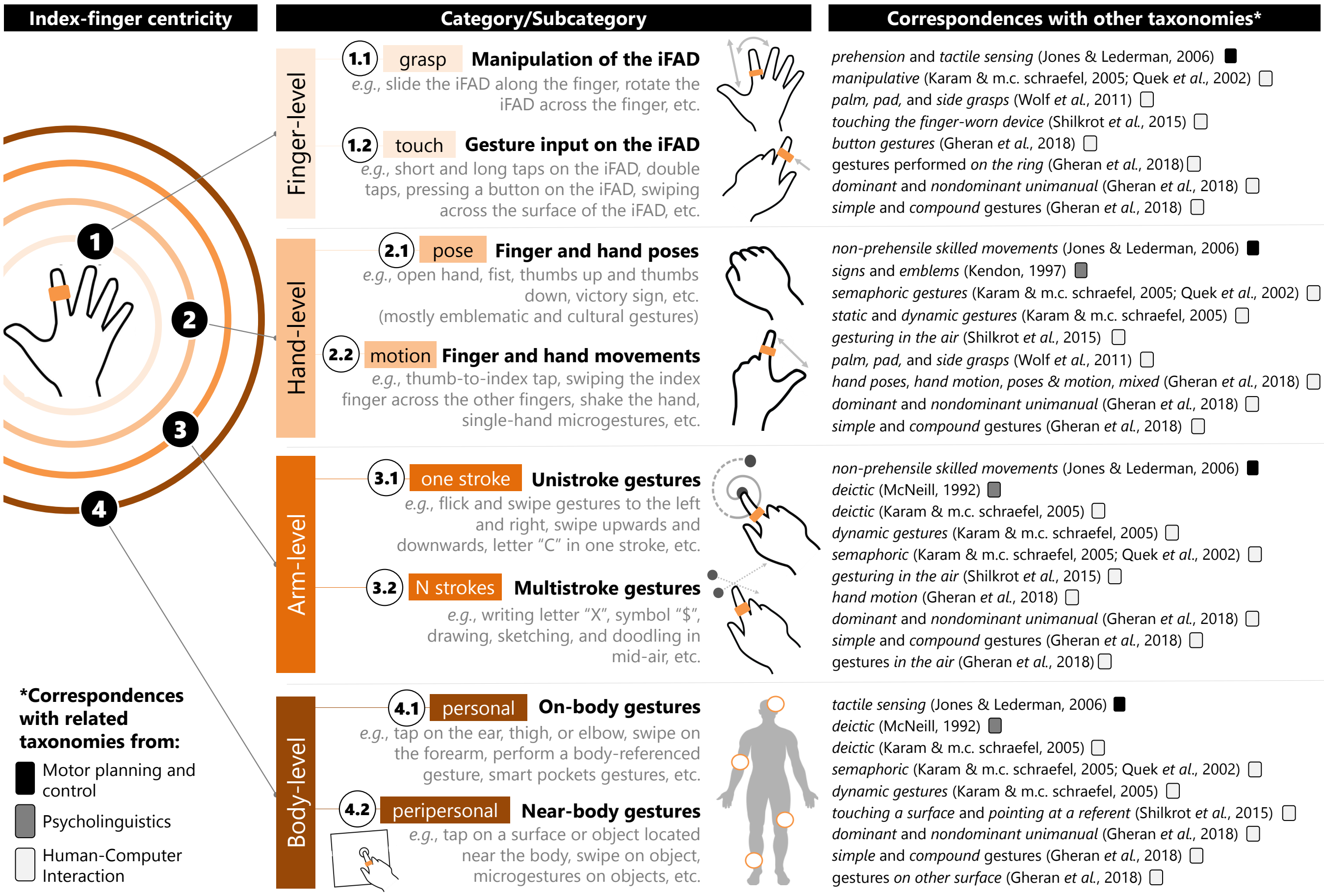


Figure 1: A four-level, technology-agnostic taxonomy of iFAD gestures illustrated according to the index finger-centric perspective and the body scale at which iFAD gestures are fully specified.

majority address prehensile movements of the hand and, thus, connect little to our scope. For example, Jones and Lederman's [53] "sensorimotor continuum" conceptualizes a range of hand functions: *tactile sensing* (the passive hand receives information when in contact to an object), *active haptic sensing* (the hand moves voluntarily over an object to collect information), *prehension* (hand reaches to and grasps objects), and *non-prehensile skilled movements* (pointing, aiming, and gestures that integrate with speech). Finger-level ❶ gestures that involve manipulation of the iFAD are *prehensile*, while hand ❷ and arm-level ❸ gestures are *non-prehensile skilled movements*. Although such correspondences with a taxonomy from motor control are useful to reveal nuances of iFAD gestures, the sensorimotor continuum [53] is too generic for HCI practitioners.

3.3.2 Psycholinguistics. Researchers have studied human gestures in relation to speech and proposed several classifications. Probably the most influential ones come from McNeill [74] and Kendon [57]; see Abner et al. [1] for an overview. McNeill [74] distinguished among four types of gestures that accompany speech: *iconic* gestures present images of concrete entities and/or actions, *metaphoric* gestures give form to abstract content, *deictic* gestures specify pointing, and *beats* are rhythmic flicks of the hand following the prosodic peaks of speech. Kendon [57] examined gestures according to their integration with speech and identified several categories, which were organized by McNeill [74, p. 37] into "Kendon's continuum." Unfortunately, these classifications are little useful to our scope since they focus on gesture meaning in relation to speech. Nevertheless, correspondences exist with the iFAD categories: Neill's *deictics* are covered by our arm-level ❸ gestures, and Kendon's *emblems* and *signs* are represented in the hand-level ❷ category.

3.3.3 Human-Computer Interaction. Karam and schraefel [55] proposed a taxonomy of gestures in HCI with *deictic, gesticulation, manipulation, semaphores,* and *sign language* categories. In relation to this taxonomy, all iFAD gestures are *semaphoric*, because they implement commands specified a priori via a dictionary [85]; finger-level ❶ gestures that involve grasping the iFAD are *manipulative*; and the classification of gestures into *static* or *dynamic* is reflected in our hand-level ❷ subcategories, where either the pose or motion of the index finger is key to specifying the gesture. Another influential taxonomy, due to the popularity of gesture elicitation studies, comes from Wobbrock et al. [122]. Originally introduced for surface gestures with four dimensions (*form, nature, binding,* and *flow*), the taxonomy has been adopted and adapted to other

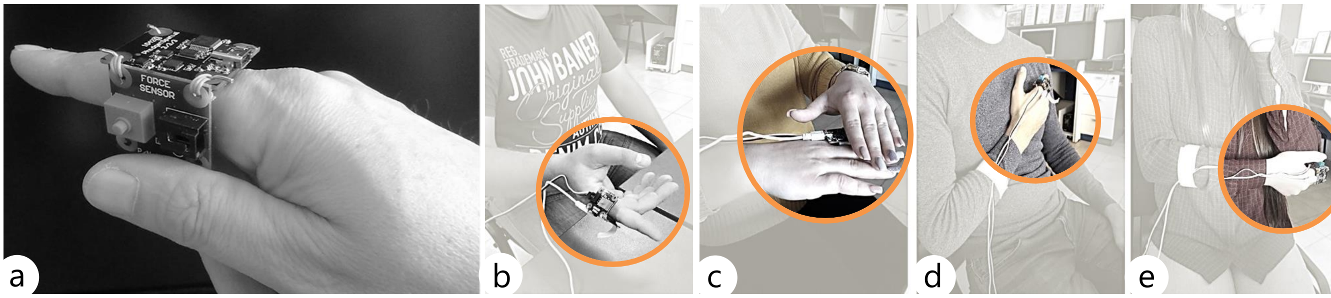


Figure 2: Custom iFAD (a) and photographs of participants performing iFAD gestures in our experiment (b-e).

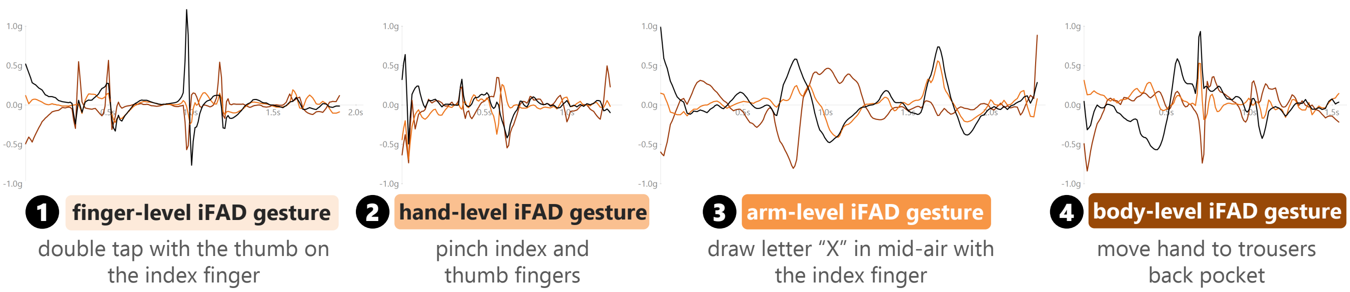


Figure 3: Examples of iFAD gestures from each category of our taxonomy, represented as linear x, y, and z-axis accelerations.

gesture types [31,92,103,129], of which a version from Gheran et al. [31] for gestures performed with electronic rings is closest to our scope. Although useful to highlight nuances of iFAD gesture articulation, such as their unimanuality, Gheran et al.'s taxonomy focuses on rings exclusively and ignores other iFAD form factors [95,110] and, correspondingly, design opportunities for other gesture types. Other taxonomies are specific to input devices and/or applications, such as pen [5] phone [92], cooperative [75], shoulder [103], or head [129] gestures and, thus, little relevant to the scope of iFADs.

3.4 Summary

Existing gesture taxonomies are either too generic or specialized for the practical need of specifying the spectrum of iFAD gestures. However, we argue that this spectrum is large and important enough (quality property Q_4) to call for its own taxonomy due to the many capabilities of the index finger. Next, we present an experiment designed to collect empirical evidence to substantiate the quality properties Q_1 to Q_3 by evaluating users' performance with and perceptions of a variety of iFAD gesture types.

4 EXPERIMENT

We conducted a controlled experiment to gain insight into the user performance with and perception of iFAD gestures.

4.1 Participants

Twenty participants (12 male, 8 female), aged between 19 and 68 years (M=27.7, SD=12.2 years), volunteered for our experiment. They were recruited by convenience sampling, word of mouth, and local advertising at our university. Participants' occupations were diverse, including students, researchers, security officer, translator.

4.2 Apparatus

We prototyped an iFAD using a PhidgetSpatial Basic sensor[1] to measure the linear acceleration of the index finger's movement and a Phidgets Force Sensor[2] to act as a button for gesture start/end events; see Figure 2a. The two sensors were connected with a lightweight cable to a Phidgets Interface Kit,[3] which transmitted the data via USB to our custom C# software application running on a Windows laptop. The cable was fastened on the forearm with a velcro strap, visible in Figures 2d and 2e, and the Phidgets kit was placed on the table near the laptop to alleviate the effect of its weight on participants' gesture articulations. Figure 3 shows examples of iFAD gestures acquired with this device.

4.3 Gesture Set

We used our taxonomy to inform a set of 40 iFAD gestures covering all four categories ❶❷❸❹; see Table 1, which also presents correspondences with similar gestures used in the scientific literature. We considered gestures of diverse complexity (column "C" in Table 1), from simple taps on the iFAD to specific finger and hand poses, stroke-gesture articulations of shapes, letters, and symbols in mid-air, and body-referenced gestures, forming a rich gesture set to examine user performance. Note that the large size of our gesture set is intended only for the purpose of our experiment to examine the many possibilities offered by the iFAD gesture taxonomy, whereas it is likely too large for users to learn and use in a practical application. We discuss smaller gesture sets in Section 6.

[1]Product ID 1042, acceleration measurement max ±8 g and resolution 976.7μg, https://www.phidgets.com/?tier=3&catid=10&pcid=8&prodid=1025
[2]Product ID 1106, https://www.phidgets.com/?tier=3&catid=6&pcid=4&prodid=76
[3]Product ID 1018, https://www.phidgets.com/?tier=3&prodid=17

Table 1: The set of iFAD gesture types used in our experiment.

Gesture name	Cat.†	Description	Correspondences	C‡	Diff.[1]	Pref.[2]	Acc.[3]
❶ **finger-level iFAD gestures**							
1. Tap	❶	Perform a tap on the iFAD	[77,86,97,117,128]	2	1.2	2.1	0.9
2. Double tap	❶	Tap the iFAD twice	[77,82,86]	3	1.4	3.5	0.8
3. Back tap	❶	Tap on the back of the iFAD with palm upward	variation of gesture #1	2	1.7	5.0	0.8
4. Double back tap	❶	Tap the iFAD twice on the back with palm upward	variation of gesture #2	3	1.8	6.1	0.8
5. Twist left	❶	Slightly rotate the iFAD to the left and rotate back	[4,20,21,39]	4	1.4	5.0	0.9
6. Twist right	❶	Slightly rotate the iFAD to the right and rotate back	[4,20,21,39]	4	1.6	5.2	0.9
7. Twist left-right	❶	Slightly rotate the iFAD to the left, right, then back	variation of #5 and #6	5	1.9	7.4	0.8
8. Twist right-left	❶	Slightly rotate the iFAD to the right, left, then back	variation of #5 and #6	5	1.9	8.1	0.8
9. Pull	❶	Slightly pull the iFAD along the finger	[4,21]	3	1.9	5.9	0.8
10. Pull twice	❶	Perform the "pull" gesture two times in a row	variation of gesture #9	4	2.0	6.9	0.7
❷ **hand-level iFAD gestures**							
11. Fist	❷	Make the closed fist hand pose	[119,120]	1	1.4	4.7	0.8
12. Vertical palm	❷	Hold palm vertically with all fingers fully stretched	[14,119]	1	1.8	7.1	0.7
13. Horizontal palm	❷	Hold palm horizontally with fingers fully stretched	[14,119]	1	1.9	7.8	0.7
14. Lateral palm	❷	Hold palm to the right of the body, fingers stretched	[14,119]	1	1.8	7.9	0.7
15. Pinch	❷	Touch the thumb and index fingers	[6,10,14,29,102,119,130]	3	1.1	2.6	0.9
16. Pinch twice	❷	Perform the "pinch" gesture two times in a row	variation of gesture #15	4	1.1	3.7	0.9
17. Shake	❷	Shake the hand wearing the iFAD	[128]	2	1.2	3.9	0.8
18. Shake twice	❷	Perform the "shake" gesture two times in a row	variation of gesture #17	3	1.3	5.0	0.8
19. Knob rotate left	❷	Hand rotates imaginary knob in mid-air to the left	[31]	5	1.7	5.0	0.8
20. Knob rotate right	❷	Hand rotates imaginary knob in mid-air to the right	[31]	5	1.5	6.2	0.8
❸ **arm-level iFAD gesture**							
21. Circle	❸	Draw a circle in the vertical plane in front of the body	[19,89,128,131,134]	5	1.2	3.5	0.8
22. Square	❸	Draw a square in mid-air	[19,97,119,133,134]	4	1.4	5.9	0.8
23. Heart	❸	Draw a heart in mid-air	variation of shape	6	1.7	7.6	0.7
24. Letter "X"	❸	Draw letter "X" in mid-air	[54,58,89]	2	1.7	7.0	0.7
25. Letter "M"	❸	Draw letter "M" in mid-air	[19,133]	4	1.6	7.4	0.7
26. Letter "S"	❸	Draw letter "S" in mid-air	variation of letter	3	1.3	6.3	0.7
27. Check	❸	Draw the "check" symbol in mid-air	[58,89]	2	1.3	3.5	0.9
28. Question mark	❸	Draw the "question mark" symbol in mid-air	[131]	3	1.4	5.8	0.8
29. Swipe left	❸	Quick stroke of the hand wearing the iFAD to the left	[19,127,128,131,133]	1	1.2	3.8	0.9
30. Swipe right	❸	Quick stroke of the hand wearing the iFAD to the right	[19,127,128,131,133]	1	1.2	4.4	0.9
❹ **body-level iFAD gestures**							
31. Left ear	❹	Bring the hand wearing the iFAD to the left ear	[80,97]	3	1.6	4.2	0.8
32. Right ear	❹	Bring the hand wearing the iFAD to the right ear	[80,97]	3	1.5	4.2	0.8
33. Mouth	❹	Bring hand with the iFAD to the mouth	[31]	3	1.3	3.8	0.8
34. Elbow	❹	Bring hand with the iFAD to the elbow	variation of [79,80,97]	2	1.5	6.0	0.8
35. Back neck	❹	Bring the hand with the iFAD to the back of the neck	variation of [79,106]	4	1.6	7.1	0.8
36. Trousers front pocket	❹	Put the hand with the iFAD in trousers front pocket	[106]	3	1.8	5.5	0.9
37. Trousers back pocket	❹	Put the hand with the iFAD in trousers back pocket	[106]	4	1.9	7.5	0.8
38. Shirt pocket left	❹	Bring the hand with the iFAD to left shirt pocket*	[106]	2	1.5	5.3	0.9
39. Shirt pocket right	❹	Bring the hand with the iFAD to right shirt pocket*	[106]	2	1.6	5.4	0.9
40. Join hands	❹	Join the two hands in front of the body	[58,128]	4	1.4	6.1	0.7

†The categories are ❶ to ❹ from our taxonomy of iFAD gestures illustrated in Figure 1.

‡The Complexity of a gesture is computed by starting from 0 and adding +1 for (i) each finger, other than the index, or body part required to perform the gesture, (ii) the number of segments of the gesture, and (iii) the number of "unusual" constituents of the gesture (i.e., specific hand poses, synchronization required between hand pose and movement, and hand movement at the back of the body)—three criteria highlighted in Xia et al.'s [126, p. 37:17] survey of gesture complexity evaluation methods used in the scientific literature. For finger ❶ and hand-level ❷ gestures, the number of segments is either 1 or 2 (e.g., 2 for "pull twice"); for arm-level ❸ gestures, the number of segments is given by Isokoski's [49] geometric complexity (e.g., 4 is the minimum number of straight lines to represent letter "M"); for body-level ❹ gestures, the number of segments is expressed in terms of regions from McNeill's [74] "gesture space" that are traversed by the hand movement (e.g., to perform "left ear," the hand traverses the center and periphery regions). We report the complexity score as an informative measure about the diversity of the iFAD gesture types selected for each category.

*If the pocket was not present, participants were asked to place their hands at the corresponding location on their body.

[1]Diff.=Perceived execution difficulty, between 1 (very easy) and 5 (very difficult to execute); lower is better; [2]Pref.=Rating of gesture preference, between 1 and 10, for each category of gestures; lower is better; [3]Acc.=Social acceptability as the willingness to perform the gesture in public, between 0 and 1; higher is better; see Section 5.

4.4 Task

The participants first engaged in a practice session to get familiarized with the iFAD and the set of gestures by performing each gesture twice (40×2=80 trials). The gestures were presented with the short text descriptions from Table 1 on the laptop where our custom data collection software was running. The meaning of each description, e.g., "circle" or "back tap," was clarified during the practice session, if needed, e.g., "A 'back tap' means tapping once on the back of the device." The participants were given total freedom on how to articulate the gestures in terms of the direction of movement for stroke gestures, force for taps, etc. The only instructions were to perform gestures at a normal speed and use the iFAD button to segment them: one press with the thumb when starting the gesture and another to signal its end. Our application logged acceleration data during these two button events. The participants started performing the gesture on the first button press and ended it on the second, a synchronization task that they practiced during the training session. In the actual data collection stage, each gesture was presented for 8 times during 40×8=320 trials. The order of the gestures was randomized per participant. At the end, the participants filled out a questionnaire; see the measures described next.

4.5 Measures

We employed six measures to characterize the objective performance and subjective perception of iFAD gestures. We computed the objective measures from the numerical gesture representations ($g = \left\{\left(a_i = (a_{ix}, a_{iy}, a_{iz}), t_i\right), i = 1..n\right\}$, where n is the number of points of gesture g, after removing the influence of the force of gravity with a high-pass filter[4] and resampling at 100 Hz (see Figure 3 for examples of the gestures collected in our experiment):

(1) Production-Time, ratio variable, measures the time to articulate a gesture, in milliseconds, between two consecutive button presses on the iFAD. Gesture production time represents a fundamental measure of user performance with gesture input and an instance of the generic "Task Time" measure employed for user evaluations in HCI; see a detailed discussion in Leiva et al. [64] and Cao and Zhai [11].

(2) Mean-Acceleration, ratio variable, measures the average magnitude, in m/s^2, of the linear acceleration of the index-finger movement during the articulation of an iFAD gesture:

$$\text{Mean-Acceleration}(g) = \frac{1}{n}\sum_{i=1}^{n}\left(a_{ix}^2 + a_{iy}^2 + a_{iz}^2\right)^{\frac{1}{2}} \qquad (1)$$

Acceleration-based features [8,84,96], from which we selected the mean composite acceleration, provide information about the physical effort to articulate the motion path of the gesture. The measure from Eq. 1 has also been referred to in the literature as gesture strength [46] or energy [87].

(3) Recognition-Accuracy, ratio variable, measures the accuracy of a gesture Recognizer, e.g., the Nearest-Neighbor classifier with the DTW dissimilarity function [101]; details about this measure follow in Subsection 5.6.

To elicit participants' subjective reactions to the iFAD gestures they had performed, we evaluated the following three measures using the questionnaire filled out after the gesture collection procedure:

(4) Perceived-Difficulty, ordinal variable, evaluates the execution difficulty of a gesture on a 5-point Likert scale with items from 1 ("very easy to execute") to 2 ("easy"), 3 ("moderate"), 4 ("difficult"), and 5 ("very difficult to execute"). We adopted this measure from Vatavu et al.'s [113] study on the perceived difficulty of stroke-gesture input.

(5) Preference-Ranking, ordinal variable, ranks the iFAD gestures in each category of our taxonomy from 1 (the most preferred) to 10 (the least preferred gesture), following the gesture ranking measure from Vatavu et al. [113].

(6) Social-Acceptability, binary variable, measures the willingness to perform iFAD gestures in front of a specific Audience (independent variable, six conditions: *alone, partner, friends, work colleagues, strangers,* and *family*) or at a specific Location (independent variable, six conditions: *home, sidewalk, driving, passenger on the bus or train, pub or restaurant,* and *workplace*) with the statements "I am willing to perform this gesture in front of [Audience]" and "I am willing to perform this gesture at [Location]." We adopted this measure from Rico and Brewster's [87] study on the social acceptability of motion gestures. We report Social-Acceptability as a percentage, e.g., 67% of the participants are willing to perform iFAD gestures in front of *strangers.*

Note that the objective (1-3) and subjective (4-6) measures may be interrelated by evaluating the same constructs, but from different perspectives, e.g., the subjective Perceived-Difficulty of a gesture could be influenced by objective aspects of the physical effort needed to perform that gesture, also reflected by the Production-Time or Mean-Acceleration measures. Following [113], we use correlation analysis in Section 5 to explore such interrelations.

4.6 Experiment Design

Our experiment was a within-subjects design with one main independent variable, Gesture-Category, with four conditions representing the iFAD gesture categories ❶❷❸❹ from our taxonomy. We are not interested in differences between individual gesture types within categories, since we treat our set as a sample of all possible iFAD gestures.[5] However, we do report our measures for individual gesture types to provide information to practitioners about specific iFAD gestures they may wish to use in their designs. The dependent variables are the measures described in Section 4.5.

5 RESULTS

We collected 6,400 gestures = 20 (participants) × 40 (gesture types) × 8 (repetitions), from which we removed 31 (0.48%) that were empty, most likely because of button segmentation failures. The remaining 6,369 gestures were visually inspected and formed the dataset for our analysis. In this section, we report results about user performance in terms of efficiency and effort (the Production-Time and Mean-Acceleration measures) and analyze participants' self-reported perceptions (Perceived-Difficulty, Preference-Ranking, and Social-Acceptability) of iFAD gestures.

5.1 Gesture Production Time

Production times varied between 1.35s for the "shake" gesture and 2.82s for "pull twice" with a mean of 1.84s (SD=0.44s); see Figure 4. A RM-ANOVA found a statistically significant effect of Gesture-Category on Production-Time (Greenhouse-Geisser estimate of sphericity $\hat{\epsilon}$=.507, $F_{(1.522,28.924)}$=66.969, p<.001) with a large effect size (η^2=.779). Post-hoc t-tests (Bonferroni-corrected α=.05/6=.0083) showed significant differences for all pairs of categories except between finger ❶ and arm-level ❸ (p=.572) and

[4] We applied https://developer.android.com/reference/android/hardware/SensorEvent for the Production-Time and Mean-Acceleration measures. For the recognition experiments reported in Subsection 5.6, we found that removing the effect of gravity actually decreased the recognition accuracy rate of our gesture recognizers.

[5] In mixed effects models [118], the variable Gesture (not used in our study) would qualify as a random effect.

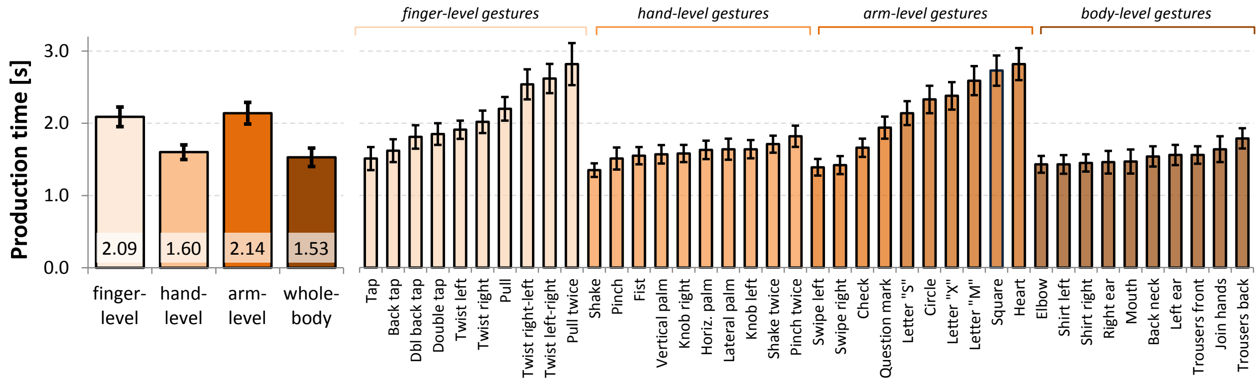


Figure 4: Mean production times for each iFAD gesture category (left) and gesture type (right). Error bars show 95% CIs.

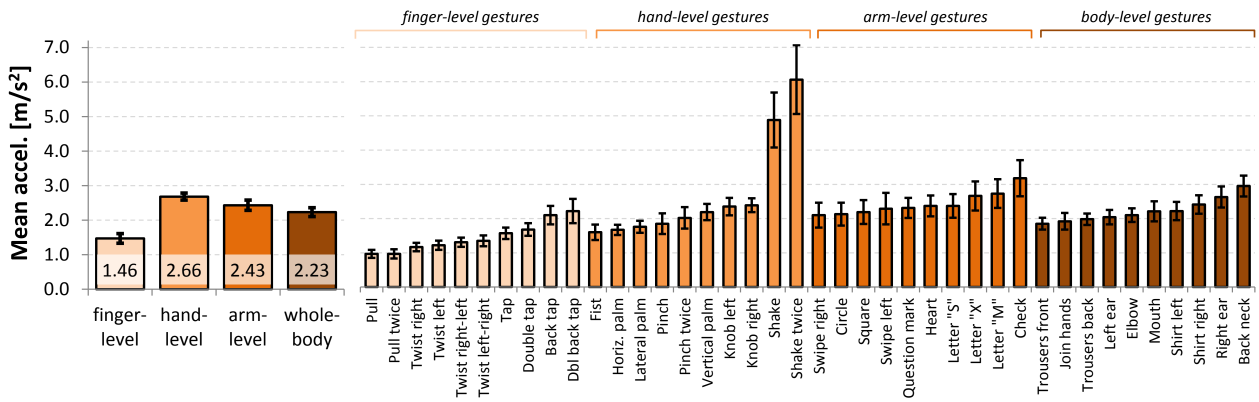


Figure 5: Mean acceleration values for each iFAD gesture category (left) and gesture type (right). Error bars show 95% CIs.

between hand ❷ and body-level ❹ (p=.026), respectively. These results show that iFAD gestures performed at finger ❶ and arm-level ❸ require on average 30% to 40% more time to produce than hand ❷ and body-level ❹ gestures, most likely because they integrate more complex gesture constituents. For example, while body-level ❹ gestures are mostly represented by ballistic movements (e.g., the hand travels directly to the left shirt pocket), arm-level ❷ gestures consist of multiple strokes, which subsume multiple ballistic movements of the hand in mid-air (e.g., letter "M" has four strokes). Also, while hand-level ❷ gestures are mostly represented by simple hand poses (e.g., vertical palm), finger-level ❶ gestures involve fine-precision movements of the fingers (e.g., grasp the iFAD to rotate it for "twist left-right") that demand more time to perform. These conjectures are supported by a significant positive correlation ($r_{(N=40)}$=.577, p<.01) that we found between Production-Time and the Complexity estimated for each gesture (Table 1). Figure 4, right shows the average production times of the individual gestures.

5.2 Gesture Mean Acceleration

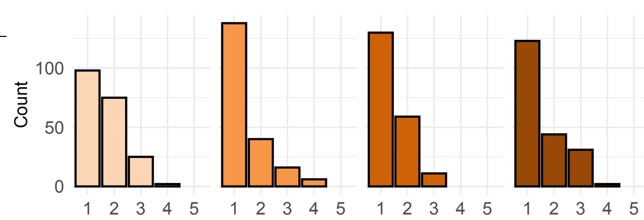
Mean acceleration varied between 0.98m/s^2 for "pull twice" and 5.95m/s^2 for "shake twice" with a mean of 2.19m/s^2 (SD=0.91); see Figure 5. A RM-ANOVA found a significant effect of Gesture-Category on Mean-Acceleration ($\hat{\epsilon}$=.606, $F_{(1.819,34.553)}$=41.199, p<.001) with a large effect size (η^2=.684). Post-hoc paired-sample t-tests (Bonferroni-corrected α=.05/6=.0083) showed significant differences for all pairs, except between hand ❷ and arm-level ❸ (p=.026) and arm ❸ and body-level ❹ (p=.166), respectively. These results show that finger-level ❶ gestures require the least amount of mean acceleration to produce (average 1.43m/s^2), while hand ❷ and arm-level ❸ gestures the most (2.63m/s^2 and 2.39m/s^2), which can be explained by the small amplitude of the underlying movement of the index finger during finger-level ❶ gestures (e.g., the index finger barely moves during a "tap"), an aspect that is duly reflected in the magnitude of the a_x, a_y, and a_z signals (Eq. 1). Figure 5, right shows the mean accelerations computed for each gesture type. The "shake" and "shake twice" gestures are easily distinguishable with the largest acceleration of the underlying movement to produce them. However, another RM-ANOVA, conducted after we excluded these two gestures from the dataset, confirmed the statistically significant effect of Gesture-Category on Mean-Acceleration ($\hat{\epsilon}$=.506, $F_{(1.517,28.822)}$=31.638, p<.001).

5.3 Perceived Difficulty

Perceived-Difficulty ratings varied between 1 ("very easy to execute") and 4 ("difficult") with a median of 1 (M=1.52, SD=0.48). A

Table 2: Perceived difficulty to perform iFAD gestures from each category; see Table 1 for the mean rating of each gesture type.

Gesture category	Rating† Mean	Mdn	SD
❶ finger-level gestures	1.66	2	0.51
❷ hand-level	1.45	1	0.49
❸ arm-level	1.40	1	0.46
❹ whole-body level	1.56	1	0.67
All categories ❶❷❸❹	**1.52**	**1**	**0.48**



† 1-very easy to execute, 2-easy, 3-moderate, 4-difficult, 5-very difficult to execute. The histograms on the right show the number of ratings out of 200 responses=20 (participants)×10 (gestures per category).

Location	Gesture category finger-level	hand-level	arm-level	whole body	
driving	0.46	0.76	0.59	0.62	**0.61**
restaurant	0.73	0.64	0.64	0.66	**0.67**
bus/train	0.76	0.68	0.64	0.74	**0.71**
sidewalk	0.76	0.64	0.72	0.76	**0.72**
workplace	0.92	0.83	0.76	0.78	**0.82**
home	0.98	1.00	1.00	1.00	**1.00**
mean	**0.77**	**0.76**	**0.73**	**0.76**	**0.75**

Audience	Gesture category finger-level	hand-level	arm-level	whole body	
alone	0.95	0.95	0.95	0.95	**0.95**
colleagues	0.84	0.79	0.76	0.78	**0.79**
family	0.92	0.94	0.96	0.94	**0.94**
friends	0.92	0.87	0.86	0.84	**0.87**
partner	0.98	0.98	0.98	0.98	**0.98**
strangers	0.68	0.64	0.65	0.72	**0.67**
mean	**0.88**	**0.86**	**0.86**	**0.87**	**0.87**

Figure 6: Mean values of the social acceptability of iFAD gestures according to various locations (left table) and audiences (right table). The mean percent of social acceptability, computed across all of the Audience and Location conditions, is 81.0%.

RM-ANOVA indicated a statistically significant effect of Gesture-Category ($\hat{\epsilon}$=.820, $F_{(3,57)}$=3.248, p=.028) of medium size (η^2=.146). However, differences were small across the four categories as the mean ratings varied between 1.40 and 1.66 on a scale from 1 to 5; see Table 2. Post-hoc comparisons indicated a significant difference (Bonferroni-corrected α=.05/6=.008) just between finger ❶ and arm-level ❸ gestures, which likely reflects the difference in perception between fine-precision and gross movements. However, the median values for these two categories were "easy" and "very easy." Across all categories, 88.4% of the ratings were either "very easy" or "easy" to execute; see the column "Diff." from Table 1.

5.4 Social Acceptability and Willingness to Use

Mean Social-Acceptability was 75% according to Location and 87% according to Audience; see Figure 6. We did not find a significant effect of Gesture-Category on Social-Acceptability ($F_{(3,57)}$=0.494, p=.688, *n.s.*), but we detected an effect of Location ($\hat{\epsilon}$=.488, $F_{(2.442,46.406)}$=11.001, p<.001) and an interaction between Gesture-Category and Location ($\hat{\epsilon}$=.371, $F_{(5.567,105.777)}$=4.053, p<.001). Also, we did not find a significant effect of Gesture-Category on Social-Acceptability ($F_{(3,57)}$=0.325, p=.808, *n.s.*), but we found a significant effect of Audience ($F_{(3.094,58.788)}$=11.478, p<.001, $\hat{\epsilon}$=.619) yet no interaction with Gesture-Category ($\hat{\epsilon}$=.288, $F_{(4.318,82.049)}$=0.809, p=.531, *n.s.*). These results suggest that Location and Audience, and not aspects intrinsic to the Gesture-Category, primarily influence the perception of social acceptability. Thus, iFAD gestures, represented by frequently used movements of the index finger, are likely to integrate user behavior naturally as our participants showed high willingness (81% on average, across both Audience and Location) to perform them in public.

Correlate	Gesture category finger-level	hand-level	arm-level	body-level	all
Execution difficulty	.936**	.954**	.681*	.437	**.756****
Social acceptability	-.736*	-.762**	-.738*	-.280	**-.682****
Production time	.770**	.273	.717*	.413	**.438****
Mean acceleration	-.248	-.164	.347	-.267	**-.045**

Figure 7: Spearman correlations with Preference-Ranking. Significant results are highlighted at p=.05 (*) and p=.01 (**).

5.5 Gesture Rankings

We asked our participants to rank the ten iFAD gestures from each category from 1 (the most preferred) to 10 (the least preferred). Column "Pref." from Table 1 lists the mean ranking of each gesture type. We did not provide specific instructions to the participants regarding this measure in order to get a glimpse into their internal models of what makes a gesture "preferable" to others. To understand the results, we performed correlations with Perceived-Difficulty and Social-Acceptability, two measures for which the instructions were specific; see Figure 7 for the results. We found a significant positive relationship with Perceived-Difficulty ($r_{(N=40)}$=.756, p=.01): the more difficult a gesture was perceived, the least it was preferred. We also found a significant negative relationship with Social-Acceptability ($r_{(N=40)}$=−.682, p=.01): the more socially acceptable a gesture was rated, the more it was preferred.

We also performed correlations between participants' subjective preference rankings and the objective measures of gesture articulation. We did not find a significant correlation between Mean-Acceleration and Preference-Ranking ($r_{(N=40)}$=−.045, p=.781, *n.s.*), which suggests that either the mean composite acceleration

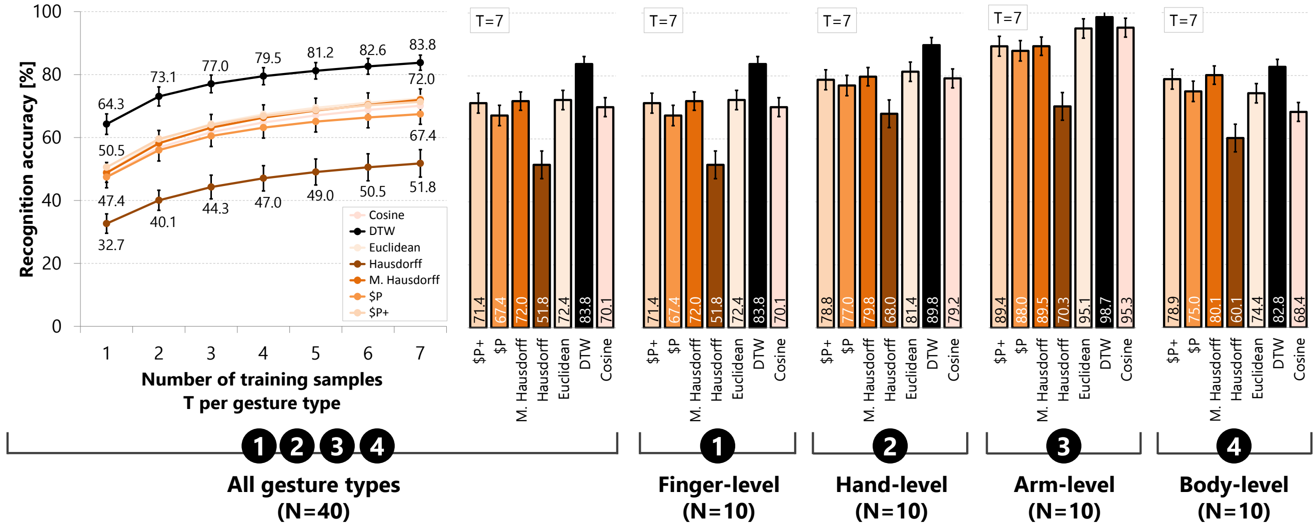


Figure 8: Recognition accuracy rates of several popular gesture dissimilarity functions for the set of 40 iFAD gesture types (left) and for each gesture category (right). The vertical bars (right) show mean accuracy rates for T=7; error bars show 95% CIs.

of a gesture is not a relevant predictor of the physical effort to produce iFAD gestures or the physical effort of gesture articulation weighed little in participants' preferences for iFAD gestures. Further examination of this aspect, including using other measures [44], is left for future work. However, we found a significant positive linear correlation between Production-Time and Preference-Ranking ($r_{(N=40)}$=.438, p=.005): gestures that took less time to produce were more preferred, a result that extends the findings of Vatavu et al. [113] from touch gestures to iFAD gestures.

5.6 Recognition Accuracy Rates

To find out how various gesture recognizers perform on our large iFAD dataset, we considered the Nearest-Neighbor approach [116, p. 93], popularized in the HCI community by the $-family [2,108, 121,123], for which we chose several dissimilarity functions with increasing levels of flexibility in how gesture paths are matched:

- *Euclidean* distance, employed by the $1 [123], $N [2], and SHARK^2 [63] recognizers, extended for 3D [81,104].
- *Dynamic Time Warping (DTW)*, a popular dissimilarity function for 3D gesture recognition [69,101,104].
- *Point-cloud dissimilarity*, introduced by the $P [108] recognizer, easily extendable to 3D [81].
- A *variant of the point-cloud dissimilarity* function, introduced by $P+ [105], and extended to 3D gestures [81]. Unlike the 1-to-1 point matchings of $P, $P+ allows N-to-M matchings.
- *Angular cosine metric*, introduced by the Protractor [65] recognizer and adapted to 3D gestures [62,104].
- *Hausdorff* [91] and the *modified Hausdorff* [25] dissimilarity functions for 3D motion gestures [104].

These dissimilarity functions, representing conditions of the independent variable Recognizer, have the advantage of being straightforward to implement in a few lines of code and require only arithmetic operations [121], which is convenient for prototyping iFADs on platforms for which little software resources (e.g., machine learning libraries) are available. We refer to prior work [62,81,101,104] for the implementation details of these dissimilarity functions.

We implemented a full cross-validation procedure to compute accuracy rates. Each gesture from the dataset was employed as a candidate for classification, for each we selected T templates at random (T varies from 1 to 7) and computed the accuracy rate by repeating the selection procedure for 100 times for each candidate and T. Overall, we present recognition results from 7 (Recognizers) × 7 (conditions for the number of training samples T per gesture type) × 100 (repetitions for each T) × 6,369 (gesture candidates submitted to classification) ≈ $3 \cdot 10^7$ classification trials.[6]

Figure 8, left shows the mean accuracy rates for each Recognizer function of the number of training samples T. A RM-ANOVA revealed a main effect of Recognizer ($\hat{\epsilon}$=.427, $F_{(2.561,46.094)}$=168.301, p<.001, η^2=.903) and T ($\hat{\epsilon}$=.218, $F_{(1.306,23.510)}$=1751.893, p<.001, η^2=.990) on Recognition-Accuracy. The highest accuracy rate was delivered by DTW (83.8% for T=7 training samples per gesture type), followed by the Euclidean (72.4%), Modified Hausdorff (72.0%), and $P+ (71.4%) dissimilarity functions. We also found a statistically significant interaction between Recognizer and T ($\hat{\epsilon}$=.095, $F_{(3.429,61.731)}$=7.864, p<.001, η^2=.304), indicating that the Nearest-Neighbor approach with different dissimilarities improves accuracy at different rates when T increases. These results indicate DTW as the best recognizer for our set of 40 iFAD gesture types, but its highest accuracy rate (83.8% for T=7 samples per gesture type) is lower than the rates reported by prior work [69,101], an effect most likely caused by the large number of gestures in our set. For example, Taranta et al. [101] evaluated DTW on a set with 25 gestures, while Liu et al. [69] used only 8 gesture types. Thus, we reran the classification procedure for each gesture category individually; see Figure 8, right for the results. The accuracy rates increased and the

[6] We removed one participant from this analysis because of missing samples that prevented computation of the accuracy rates for the conditions T=6 and T=7.

Table 3: Production time of iFAD gestures compared to other gesture types and sensing devices, shown in ascending order.

Dataset / Reference	Gesture types	Device / Implementer	Num. gestures	Num. users	Total samples	Production time [s]		
						Mean	SD	95% CI
Hoffman et al. [45]	Motion gestures	Wiimote game controller	25	17	8,500	1.01	0.21	[0.91, 1.11]
Chen et al. [16]	Motion gestures	Wiimote game controller	20	28	5,600	1.14	0.32	[1.02, 1.26]
Wobbrock et al. [123]†	Unistrokes	Stylus on iPAQ Pocket PC	16	10	1,600	1.15	0.44	[0.88, 1.43]
Anthony & Wobbrock [2]‡	Multistrokes	Stylus on Tablet PC	16	10	1,600	1.49	0.38	[1.25, 1.73]
This paper	Body-level ❹	iFAD (3-axis accelerometer)	10	20	1,596	**1.53**	**0.29**	**[1.40, 1.66]**
This paper	Hand-level ❷	iFAD (3-axis accelerometer)	10	20	1,590	**1.60**	**0.23**	**[1.50, 1.70]**
Vatavu & Ungurean [112]¶	Uni- and multistrokes	Finger on 7-inch tablet	12	35	3,779	1.75	0.58	[1.55, 1.94]
Anthony & Wobbrock [2]‡	Multistrokes	Finger on Tablet PC	16	10	1,600	2.01	0.53	[1.68, 2.34]
This paper	Finger-level ❶	iFAD (3-axis accelerometer)	10	20	1,591	**2.09**	**0.31**	**[1.95, 2.23]**
This paper	Arm-level ❸	iFAD (3-axis accelerometer)	10	20	1,592	**2.14**	**0.34**	**[1.99, 2.29]**
Vatavu et al. [111]§	Uni- and multistrokes	Finger on 10.1-inch tablet	12	27	3,249	2.90	0.90	[2.56, 3.25]
Fothergill et al. [28]	Whole-body	Kinect	12	30	5,654	3.51	0.71	[3.25, 3.76]
Vatavu [107]	Whole-body	Kinect	15	30	1,312	4.29	0.85	[3.99, 4.60]
		Total	**184**	**277**	**39,263**			

†Gestures were collected in [123] at three speeds (slow, medium, and fast), but we used just the medium condition, where participants were instructed to "balance speed and accuracy" (p. 164). ‡Medium speed condition [2]. §Gestures were collected in [111] from participants with low vision and without visual impairments, but we only use the gestures produced by the latter (27 participants without visual impairments). ¶Gestures were collected in [112] from participants with and without motor impairments, but we only use the gestures produced by the latter (35 participants without motor impairments).

ranking order of the Recognizer conditions stayed the same with DTW delivering the best performance: 83.8% accuracy for finger ❶, 89.8% for hand ❷, 98.7% for arm ❸, and 82.8% for body-level ❹ gestures. Although these accuracy rates are fairly high given our choice to use simple Nearest-Neighbor recognition techniques suitable for rapid prototyping, they should be interpreted as a lower bound of iFAD gesture recognition, whereas more powerful approaches would likely perform better. In this context, our evaluation results recommend DTW for rapid prototyping of iFAD gesture-based UIs, but careful design of gesture sets can equally make DTW highly accurate for deployment in actual applications. We provide a detailed discussion of this aspect in the next section.

6 DISCUSSION

Our results revealed that iFAD gestures are fast (between 1.53s and 2.14s on average, depending on their category), perceived as low effort (1.52 average rating on a scale from 1 to 5), and socially acceptable (81% willingness to perform them in public). These findings confirm our expectations regarding their quality properties Q_1, Q_2, and Q_3, enumerated in Section 3.1, while property Q_4 (versatility) emerges directly from the variety of iFAD gesture types. In this section, we highlight the virtues of our iFAD gesture taxonomy, discuss iFAD gestures in the larger context of gesture input performed with various devices, compile subsets of iFAD gestures that can be recognized with high accuracy, and present implications for researchers and practitioners.

6.1 Virtues of the iFAD Gesture Taxonomy

We showed in Section 3 how existing gesture classifications are either too generic or specialized to capture the diversity and nuances of iFAD gestures. Thus, one virtue of our taxonomy is to offer *descriptive systematization* of a wide spectrum of gestures captured from the vantage point of the index finger. This virtue enables gesture set design and examination within one conceptual framework, but also reinterpretation of gesture types, e.g., gestures for on-body input as iFAD gestures, from the perspective of the index finger with potential impact on the choice of technology to detect those gestures, e.g., instrumenting the index finger instead of other body parts. In Section 4, we used our taxonomy to inform a diversity of iFAD gestures for our experiment, which highlights its *generative virtue*. This virtue enables exploration of many design possibilities due to a clear structuring of possible iFAD gestures according to the body scale at which they are fully specified. To better understand the opportunities enabled by our iFAD gesture taxonomy, it is useful to examine iFAD gestures in the context of other gesture types; see next.

6.2 iFAD Gestures in Context

The production time of a gesture is an instance of the generic "Task Time" measure widely used in HCI to evaluate user performance with interactive systems; see [11,64]. Our results showed that iFAD gestures are fast, but it is informative to put these results into perspective by considering other gesture types and sensing devices. To this end, we used several public datasets to extract the production times of gestures performed with styli [2,123], fingers on touchscreens [2,111,112], game controllers [16,45], and the whole body [28,107]. Overall, we employed for this analysis a total number of 39,263 gestures of 184 types produced by 277 users; see Table 3. Our findings revealed that iFAD gestures are approximately two times faster than whole-body gestures [28,107], about as fast as stylus [2] and finger [2,111,112] multistroke gestures on mobile devices, but slower than motion gestures performed with game controllers [16,45]. While these results are informative as a first-order approximation of how iFAD gestures fare compared to gestures performed with other devices, we recommend future work for their confirmation with controlled experiments.

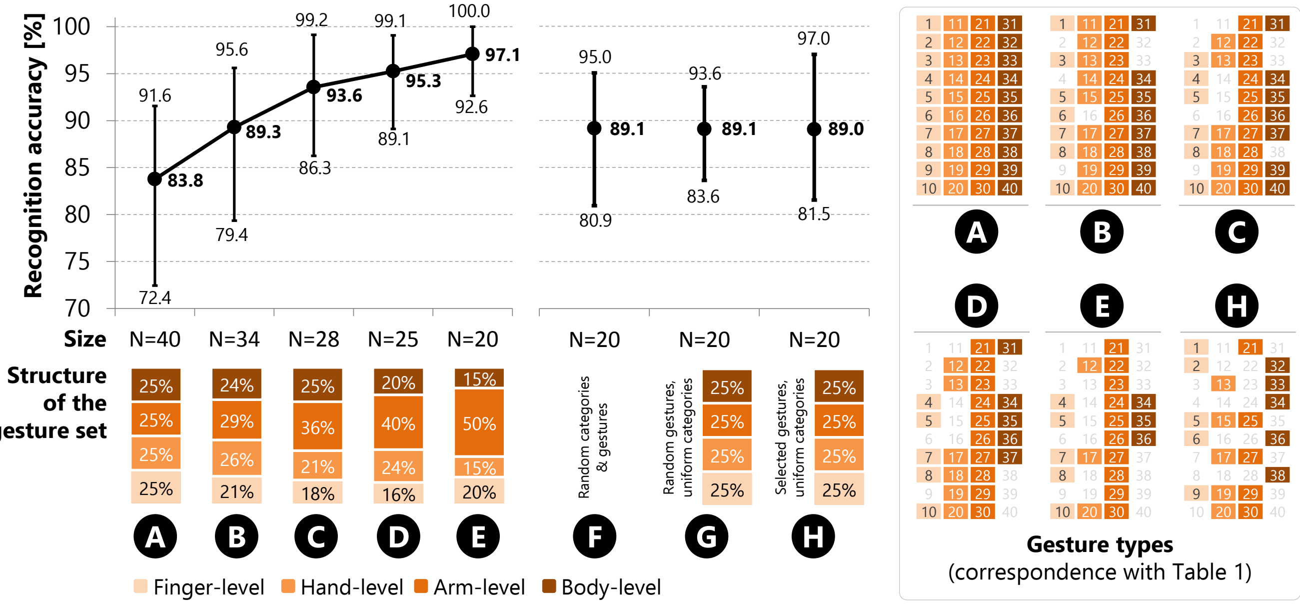


Figure 9: Recognition accuracy rates of DTW for various iFAD gesture sets. Error bars show min/max accuracy rates per user.

6.3 iFAD Gestures with High Recognition Rates

The highest accuracy rate achieved by the gesture recognizers evaluated in our experiment was 83.8% for the entire set ❶❷❸❹ of 40 iFAD gestures and 98.7% for the subset of arm-level ❷ gestures, respectively. Our choice of gesture recognizers was based on their ease of implementation and portability, especially for wearable platforms representative for iFADs. It is very likely that by using more sophisticated models, such as deep learning approaches [19, 66, 120], or other sensing dimensions, such as a 9-axis IMU compared to the 3-axis accelerometer from our experiment, recognition accuracy rates will increase. We leave such explorations for future work. For now, we are interested in whether subsets of the 40 iFAD gesture set can be recognized with high accuracy using our simple, platform-independent recognition techniques. This question is also practical from the perspective where asking users to remember 40 distinct gestures is probably too much cognitive load and may require learning techniques integrated in the user interface.

To identify a subset of highly-recognizable iFAD gestures, we analyzed the confusion matrix of the best recognizer condition (DTW with T=7) and iteratively eliminated gestures with error rates above 10%. We arrived at a first subset of 34 gestures, for which we reconducted the recognition experiment and found that accuracy increased to 89.3%; see condition "B" in Figure 9. We continued our analysis and eliminated gestures for which the error rate was larger than 5%, and arrived at 93.6% accuracy for a subset of 28 iFAD gestures, 95.3% for 25 iFAD gestures, and 97.1% for 20 iFAD gestures, respectively; see Figure 9, conditions "C," "D," and "E." The right part of Figure 9 shows the gesture types that were removed, e.g., gestures no. 1, 2, 6, 9, 11, 14, 15, 16, 32, 33, and 38 were removed in condition "C"; see numeric correspondences with Table 1. The bottom part of the figure shows the structure of the subsets, e.g., the subset of 20 gestures from condition "E" contains 20% finger-level ❶, 15% hand-level ❷, 50% arm-level ❸, and 15% body-level ❹ iFAD gestures, respectively. These results show that a subset of 20 iFAD gestures can be reliably recognized (97.1%) for practical purposes using the DTW dissimilarity function, readily implementable on any wearable platform.

We did not continue reducing the size of the gesture set below 20, because we already knew that the subset of 10 arm-level ❸ gestures could be recognized with 98.7% accuracy (Figure 8). However, to find out more, we reconducted the recognition experiment by randomly selecting 20 gesture types from the set of 40 (condition "F" in Figure 9). The average accuracy rate over 100 repeated selections was 89.1%. When we reconducted the experiment with random gestures chosen so that the four categories were equally represented (condition "G" in Figure 9), we arrived at the same result. For a final test, we cherry-picked 20 gesture types from our set that we considered both simple and intuitive, such as "tap" and "double tap," "twist left" and "twist right," "pinch," and on-body gestures, while still preserving the uniform distribution of the four iFAD categories (condition "H" in Figure 9), and obtained 89.0% accuracy. These results are promising given that the gestures were acquired solely from the vantage point of the index finger, without sensing any other part of the body. Next, we capitalize on all of our findings to present implications for researchers and practitioners.

6.4 Implications for Researchers and Practitioners

We use our theoretical contributions and empirical evidence to propose practical implications for researchers and practitioners interested in using iFAD gestures in their own projects.

6.4.1 Design gesture sets for gesture-based UIs within one conceptual framework. The iFAD gesture taxonomy, as a structured space for systematizing interactions based on the index finger, enables exploration of possible gesture types for gesture UI design, from microgestures to hand poses to mid-air swipes to on-body input. Designers should capitalize on the diversity of iFAD gestures (Q_4) towards gesture-based UIs featuring interactions that are expected to be fast (Q_1), low effort (Q_2), and highly acceptable (Q_3). The upper hand of the iFAD taxonomy stems from the incorporation of a large variety of gesture types in one conceptual framework.

6.4.2 Design gesture-based interactions from the perspective of the index finger. By adopting the vantage point of the index finger, a diversity of gestures can be reframed, e.g., a Smart-Pockets [106] on-body gesture described as an iFAD gesture. This reframing can influence the choice of technology to sense gestures, e.g., an electronic ring with motion sensing instead of a touch sensor integrated in the pocket. This implication suggests leveraging the versatility and ubiquitous use of the index finger during gesture interaction design by adopting an approach centered on the distinctive perspective offered by the index finger.

6.4.3 Use the iFAD gesture taxonomy to inform scientific experiments. Few studies from the scientific literature on gesture interaction have resorted to theoretical foundations to inform the specific gestures considered for evaluation. Unfortunately, this aspect may have affected their results (e.g., because of limited coverage of possible gesture types) and may have even introduced bias (e.g., researchers repeatedly using the same gestures in their studies or reusing gestures from other papers without a theoretical justification). The iFAD gesture taxonomy provides a structured space to inform gesture sets with a large coverage at the level of the body in scientific experiments conducted to examine user performance with gesture input of many kinds.

6.4.4 DTW for rapid prototyping and exploration of iFAD gesture-based UIs. Our empirical results showed that the Nearest-Neighbor approach with the DTW dissimilarity performed well on a diversity of iFAD gestures captured with a 3-axis accelerometer. Prior work [101] has shown that DTW-based approaches also work well with gestures captured with other devices. Thus, DTW is recommended for rapid prototyping of iFAD gesture-based UIs due to its high recognition accuracy and simple implementation that makes it portable to virtually any wearable platform. Using more complex recognition approaches [19,66,120] will likely lead to higher accuracy rates of iFAD gestures. Also, specific UI requirements, such as allowing users to articulate gestures as they wish, may need articulation-invariant gesture recognizers [105,108,109], aspects to be examined closely in future work.

6.4.5 Adopt a hybrid gesture set design approach for gesture-based UIs. To complement the design perspective centered on the index finger, we suggest design that juxtaposes gesture input performed with the index finger with other gesture types by exploiting the correspondences between our iFAD gesture categories and other gesture taxonomies, illustrated in Figure 1. A hybrid approach opens new design possibilities that would benefit from the versatility of iFAD gestures, but also the specifics of other gesture types, e.g., pen gestures [5], phone gestures [92], head gestures [129], etc. It also includes design for two iFADs toward bimanual gestures for cross-device [17] and composite wearable [60] input.

7 LIMITATIONS

There are a few limitations to our experiment, which we acknowledge in this section to suggest opportunities to address them in future work and examine iFAD gestures in more detail. First, we collected gestures using an iFAD with a specific form factor resembling a ring, but other form factors, e.g., ring-like and ring-ready devices [110], are interesting to examine in future work. Second, our device incorporated a 3-axis accelerometer, which is convenient for the practical purpose of prototyping iFADs since such sensors are low-cost and widely available (e.g., the MPU-6050 6-axis gyroscope and accelerometer costs about USD $5[7]), but other sensors should equally be examined to detect iFAD gestures. Third, an examination of false positives during continuous gesture recognition, using for example the technique from [100], will complement our findings on recognition accuracy rates, as will collecting gestures in other contexts, e.g., when walking and during everyday activities [34], or for more on-body locations susceptible of lower social acceptance [41]. We leave such interesting explorations about both user and system performance with iFAD gestures for future work.

8 CONCLUSION

We examined gestures of the index finger sensed with iFADs. Our results showed that iFAD gestures are fast, low effort, and socially acceptable, while sets of 10 to 20 iFAD gestures can be accurately recognized with simple recognition approaches, straightforward to implement on wearable platforms. Our iFAD gesture taxonomy, introduced to structure the spectrum of possible iFAD gestures, could also be exploited to inform application gesture sets, from microgestures to whole-body input, within one conceptual framework that leverages the vantage point of the index finger, but also to enable explorations of possible connections with other gesture classification systems toward richer gesture input for interactive systems. To encourage more discoveries and future work on iFADs, but also to enable replications [48], including extensions and repurposing studies [32] with new gesture measures computed from acceleration data [45,50], we adhere to the transparency of CHI research artifacts [114] and release our dataset (6,369 samples of 40 gesture types collected from 20 participants) together with C# source code that reads the data and computes the measures reported in this paper. Our resources are freely available to download from the web address http://www.eed.usv.ro/~vatavu.

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