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ORIGINAL PAPER

Characterizing gesture knowledge transfer across multiple contexts of use

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Abstract We address in this work interactive gestures as a distinct type of *knowledge* that users acquire and employ when interacting in smart environments. We characterize the problem of *gesture knowledge transfer* by describing gesture knowledge at the user level with the new IUES box concept (information, understanding, experience, and skill), and we introduce the new AIS space (articulation, interpretation, and sensing) to characterize gesture knowledge transfer across multiple contexts of use. Our explorations will be useful to researchers and practitioners of smart environments that wish to reuse people's gesture knowledge for intuitive gesture-based interactions in such spaces.

Keywords Gesture interaction · Gesture knowledge · Knowledge transfer · Smart environments

1 Introduction

As human sensing technology develops in terms of high-precision sensors, miniaturized wearables, and sophisticated algorithms that process sensor data fast and reliably, smart environments become more aware of their users' goals and actions. In fact, the profusion of sensors available today enable researchers and practitioners to implement smart environments that come very close to the vision of ambient intelligence, in which environments are context aware and services provided to users are personalized, adaptive, and anticipatory [1]. Although such environments can capture a wealth of useful data about their users' presence, location, and actions, designing intuitive interactions for such spaces is nevertheless challenging.

In this work, we make one step forward toward addressing this challenge by examining *interactive gestures as a distinct type of knowledge* that users acquire, develop, and employ in such smart spaces. As with any type of knowledge, gesture knowledge can be accumulated and reused for new interactions in new environments. To this end, we define the concepts of *gesture knowledge* and *gesture knowledge transfer* for multiple contexts of use. We rely on results from epistemology [2] and the organizational theory [3–7] to derive a taxonomy of gesture knowledge, which we describe in terms of information, understanding, experience, and skills with our new IUES box concept. We conjecture that gesture knowledge at the level of the *individual* results from the cognitive processing of successful experiences of effective and efficient gesture production, while gesture knowledge transfer occurs at the *social* level from effective combination of individual IUES boxes mediated by collaborative gesture production [4,8,9]. To describe the later, we introduce a new space for characterizing gesture knowledge transfer (AIS), for which we identify three important dimensions: articulation, interpretation, and sensing.

The contributions of this work are as follows: (1) we introduce the concept of *gesture as knowledge* and conduct a characterization of *gesture knowledge transfer*, for which we describe an individual's gesture knowledge with the new IUES box concept; (2) we discuss a taxonomy of gesture knowledge by inspiring from epistemology and organizational theory, and we introduce the new AIS space to characterize gesture knowledge transfer; (3) we show the usefulness of our concepts with practical examples and real-

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world data of stylus gesture input, motion gestures, and mid-air gestures.

2 Related work

We relate in this section to previous work on gesture interaction in smart environments, we discuss the concepts of knowledge and knowledge transfer, and we provide a brief overview of gesture innate knowledge.

2.1 Gesture interaction in smart environments

Gesture user interfaces are attractive for designing interactions in smart environments as they provide users with natural, flexible, and intuitive ways to communicate intentions and execute commands. Notable applications include control of smart homes [10–12] and interacting with ambient displays [13–16]. Gesture recognition has been implemented with many machine learning approaches; see [17–20] for surveys on gesture acquisition and recognition for various application domains. New software infrastructure for recognizing gestures in smart environments has also been proposed, such as WS-Gesture [21], gesture profile for web services (GPWS) [22], and gesture services for cyber-physical environments (GS-CPE) [23].

One challenging aspect of designing gesture interactions is to find a good mapping between gesture commands and the functions they execute. The literature has shown that users have different gesture preferences [12,24,25] and that variability exists in gesture articulation [26–30]. For instance, Rekik et al. [27,28] showed that users vary their multi-touch gestures in terms of number of fingers and the way hands move in parallel or in sequence. Also, gesture production in public spaces depends on location and audience [31,32] and the social acceptance of gestures is influenced by culture, time, and interaction type [33].

The idea of reusing people's experience to interact using gestures has been considered before by Vatavu [34,35], who introduced the concepts of "nomadic gestures" and "smart pockets." Nomadic gestures are training samples that reside on their owner's smart device and are uploaded to the interactive system prior to the actual interaction. Nomadic gestures enable reuse of gesture commands in any smart environment by automatically remapping users' preferred gestures with the available tasks to execute in that environment. Smart-Pockets implement fast retrieval of personal digital content with hand gestures reaching for physical pockets on clothes. The smart-pockets metaphor enables links to digital content using physical personal containers that have been devised over decades of fashion design to provide convenient access to one's personal belongings.

2.2 Knowledge and transfer of knowledge

The definition of knowledge has been an ongoing debate in epistemology. For a statement to be considered knowledge, that statement must be true, people must believe it is true, and there must be ways to justify why it is true. Knowledge and knowledge transfer have been examined in the fields of information systems and organizational theory to provide organizations with sound practices to create, capture, and distribute knowledge [6,36,37]. The literature has emphasized that *knowledge* is a distinct concept from *information* and *data* [3,4,38]. For instance, Nonaka [5] defines information as data that is interpreted into a meaningful framework, while knowledge is information that has been authenticated; Machlup [39] looks at information as a flux of messages with associated meaning that can increase or revise the knowledge of the recipient; and Alavi and Leidner [3] consider that information becomes knowledge when processed by the human mind, while knowledge can turn into information if presented in symbolic forms, such as text.

Researchers have identified and examined various types of knowledge. For instance, Nonaka [4] points to two dimensions of knowledge creation: epistemological and ontological. The epistemological dimension draws a distinction between *tacit* and *explicit* knowledge by following Polanyi's classification from philosophy [2]: explicit knowledge can be codified and transmitted in formal language, while tacit knowledge is personal and, thus, hard to formalize and communicate, but it is rooted in action, commitment, and involvement in a specific context. Other examinations of knowledge have considered conscious, explicit, automatic, and subconscious knowledge [7], declarative, procedural, causal, conditional, and relational knowledge [40], and embrained, embodied, encultured, embedded, and encoded knowledge [41,42]. By overviewing current definitions of knowledge, Alavi and Leidner [3] conclude that "knowledge is a justified belief that increases an entity's capacity for taking effective action."

Knowledge can be transfered between individuals at the level of the organization in several ways [4–6,43]. For instance, by noting that organizational knowledge is created as the result of the dialogue between tacit and explicit knowledge, Nonaka [4] proposed four models of knowledge conversion, i.e., tacit to tacit, explicit to explicit, tacit to explicit, and explicit to tacit. Wasko and Faraj [43] examined the ways in which knowledge is contributed inside networks of practice and identified three factors with the most influence on individuals' motivation to contribute knowledge: reputation (i.e., the status of an individual in the community), centrality (i.e., the extent in which an individual is in contact with others), and tenure (i.e., individuals with longer tenure have a better understanding of how their expertise is relevant in some particular context).

In this work, we are inspired by such previous developments in representing knowledge and modeling knowledge transfer, especially by the work of Nonaka [4], which we use to derive the concepts of gesture knowledge and gesture knowledge transfer.

2.3 Gesture innate knowledge

The psycholinguistic literature has examined human gesture production to understand how people communicate [44,45]. Gestures have been described and analyzed in relation to language and speech as they reveal the processes of human thought [45]. Previous work showed that speech and gestures are coded as a single signal by a unique communication system [46] and that gestures are tightly intertwined with spoken language in time, meaning, and function, creating a speech-gesture synchrony [45]. Gestures convey information to their listeners [44], communicate attitudes and emotions both voluntarily and involuntarily [47], and represent effective means for non-verbal communication between interacting partners, even at a distance [48]. Also, speakers from all cultural and linguistic backgrounds use gestures [49], while gesture communication emerges in young children even before the development of language [50]. Even more, gestures are so deeply interwoven with our thought processes that blind people gesture as they speak just as much as sighted individuals do, even when they know their listener is also blind [51]. These previous works show that there exists a form of *innate gesture knowledge* in the individual, which represents a strong motivation to pursue the development of a theory and practice of *interactive gesture knowledge*.

3 Gesture knowledge and gesture knowledge transfer: taxonomy and characterization

In this work, we understand by "gesture" any movement that bears meaning for the purpose of interacting with a computer. This generic definition enables us to consider various types of gestures, regardless of their physical instantiation and form [52], their communicative or manipulative attributes [53], functionality [54], relationship to speech and communication [45], structural patterns [55], or application domains [56,57]. The interpretation that we use is in line with other researchers, such as Buxton [58] or Vatavu [59]. Also, we follow in this work the definition principle illustrated by Kurtenbach and Hulteen [60] to discriminate between gestures and generic movement: "A gesture is a motion of the body that contains information. Waving goodbye is a gesture. Pressing a key on a keyboard is not a gesture because the motion of a finger on it's way to hitting a key is neither observed nor significant. All that matters is which key was pressed." We are thus embracing in this work various types of gesture commands, for which practitioners need to make

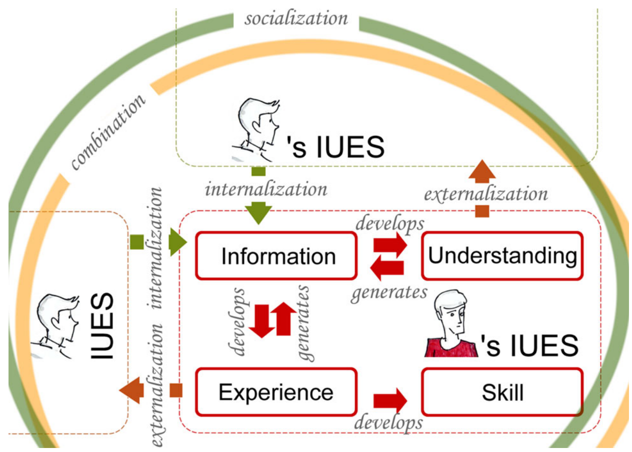

Fig. 1 An individual's gesture knowledge is represented by an *IUES box* reflecting the information, understanding, experience, and skill of that individual. Social gesture knowledge is formed by communicating *IUES boxes*, a process during which individuals share information by externalizing their knowledge and internalizing information from others

the right decisions regarding the best fit acquisition device, recognition technology, and composition of the gesture sets, as stressed by Beuvens and Vanderdonckt [56].

In the following, we introduce the concepts of *gesture knowledge* and *gesture knowledge transfer*, and we identify the factors that determine successful transfer of gesture knowledge.

3.1 Gesture knowledge

We define *gesture knowledge* as the body of information, understanding, experience, and skill (IUES) required to produce gestures effectively in a given context of use; see Fig. 1. *Information* represents data and facts about gesture production in general and gesture interfaces in particular. *Understanding* represents a mental grasp of the situation at hand, which leads to gesture action. Both *Experience* and *Skill* inform effective and efficient production of gestures, i.e., the correct gesture that will do the job effectively (experience) and the most efficient way to produce that gesture to optimize time, effort, and information conveyed (skill).

Because gesture knowledge represents one instance of generic human knowledge, we can connect the four IUES components to the classical definition of knowledge from epistemology, according to which, for a statement to be considered knowledge, that statement must be true, people must believe it is true, and there must be ways to justify that the statement is true [61]. IUES reflects all these attributes of knowledge, as follows. Information about gestures is accumulated through personal experiences which, when successful, build confidence regarding the truthfulness of information. In the absence of authoritative explanations of why things work, people build their own mental models of the situations they experience [62] and participatory design of gesture commands has exploited this fact to reveal users' mental models about gesture input [11,12,14,25].

Gesture knowledge is intrinsically connected to *gesture production*, which consists of distinctly identifiable phases, such as preparation, execution, and retraction [45]. Knowledge is needed for effective production of gestures, while the outcome of gesture production generates information useful for the performer to build further understanding, experience, and skill. Therefore, in the context of gesture-based interfaces, *gesture knowledge at the individual level results from the cognitive processing of successful personal experiences consisting in effective and efficient gesture production.*

3.2 Gesture knowledge transfer

Transfer of gesture knowledge can be defined and analyzed at the level of the individual or at level of the social community in which individuals collaborate. At the individual level, we define gesture knowledge transfer as the physical and cognitive abilities of an individual to reuse their gesture knowledge in a new context, e.g., in a new environment or with a device other than the devices on which their gesture experience has formed.

Transfer of gesture knowledge in a social group involves communication between individuals that share knowledge and create new knowledge by combination mechanisms, such as sorting, adding, restructuring, recategorization, recontextualization, etc. To exemplify gesture knowledge transfer, consider how gesture knowledge is acquired at the individual level. One way is through the formal channel of training from an authoritative source (e.g., information provided by an expert or found in user manuals) with the help of assistive systems [63–68]. Another way to acquire knowledge is by observation and experimentation in social contexts [8,13,16]. For instance, Chartrand and Bargh [69] identified the "chameleon effect," which represents "nonconscious mimicry of the postures, mannerisms, facial expressions, and other behaviors of one's interaction partners, such that one's behavior passively and unintentionally changes to match that of others in one's current social environment" (p. 893). In the context of gesture-based interfaces, *gesture knowledge transfer at the level of the individual results from successful internalization of IUES through effective and efficient gesture production*. At the social level, *gesture knowledge transfer results from effective communication between individual IUES boxes mediated by gesture production.*

3.3 A taxonomy of gesture knowledge and gesture knowledge transfer scenarios

We continue our characterization of the gesture knowledge concepts by exploring a multi-criteria taxonomy of gesture knowledge, which we construct by describing gesture knowledge along various dimensions and by identifying factors relevant for gesture knowledge transfer. We inspire our approach from organizational theory, especially from the work of Nonaka [4,6]. Although a lot of effort has been made on formalizing and characterizing knowledge and knowledge transfer [7,40,42,43,70], the work of Nonaka [4,6] with its emphasis on the importance of the personal beliefs of the individual that can be justified with working mental models of the world approaches very closely our definition of gesture knowledge. Figure 1 shows information, understanding, experience, and skill as distinct aspects of gesture knowledge captured in the IUES box as well as communicating mechanisms for IUES boxes. Nonaka's four modes of knowledge creation at the individual and social levels [4] connect to these mechanisms as follows. Transfer of tacit gesture knowledge (i.e., tacit to tacit [4]) takes place during *socialization* when people interact with each other [69] or when they share devices [8]. Explicit gesture knowledge creation at the social level (i.e., explicit to explicit [4]) takes place during *collaboration* between individuals toward the achievement of some task [9]. Internalization (i.e., explicit to tacit [4]) and externalization of gesture knowledge (i.e., tacit to explicit [4]) are effects of collaboration between individuals that need to adapt in order to be productive and effective in the group (*internalization*) and to allow others to be effective as well (*externalization*) [71,72]. In the following, we discuss various dichotomies for gesture knowledge by inspiring from Nonaka [4].

3.3.1 Tacit versus explicit gesture knowledge

Following Polanyi's work in philosophy [2] and Nonaka's [4,6] and Spender's [7] classifications of knowledge from the organizational theory, we adopt the ontological dimension of knowledge and make distinction between *tacit* and *explicit* gesture knowledge. Tacit gesture knowledge exists in the user as an individual and consists in the sum of personal experiences and mental models that the individual has formed about communicating meaningful action. Therefore, tacit knowledge is difficult to articulate, but can be easily observed in gesture production. One consequence of tacit knowledge for gesture user interfaces is the variability that accompanies gesture articulation, i.e., no two gestures are alike, but they vary in terms of geometric shape, kinematics, and structure. For example, Rekik et al. [27,28] brought empirical evidence that different users produce the same gesture types in various ways, and Anthony et al. [26] quantified numerically the within- and between-user consistency of gesture variation with a dedicated methodology. Explicit gesture knowledge represents a codifiable, transmittable resource about how to produce gestures, such as gesture diagrams [66,67], path guides [63,73], or gesture video tutorials [68]. Once an optimal gesture set has been designed, explicit knowledge can amplify its effectiveness and reach out.

3.3.2 Individual versus social gesture knowledge

In organizational theory, Nonaka [4] points out that it is the individuals that create knowledge, while the role of the organization is to articulate and amplify that knowledge. Following this line of thought, gesture knowledge has an *individual* dimension when it is created and can be *social* when adopted by a group. For example, gesture commands designed by experts are instances of gesture knowledge created at the individual level with an authoritative mark, such as the Rotate'N Translate [74] or pinch-to-zoom plus [75] techniques. Transfer in this case takes the form of internalization of knowledge from the community of experts. Another example is gestures proposed by users, which inform designers of users' preferences and mental models about gesture interaction [11,12,25]. In this case, the flow of gesture knowledge transfer is from the individual to the group in the form of externalization, i.e., users' verbalizations of their gesture actions and designers' observations of users' gesture behavior contribute to creation of new gesture knowledge.

3.3.3 Innate versus educated gesture knowledge

Examples of innate knowledge include information about general body movement by proprioception [76] or generic expectations about body movement, such as large movements require more effort than small ones. Training, trial and error, or learning from experience are ways to attain a posteriori gesture knowledge. For instance, after several failed attempts, users think of new ways to perform a task [77]. Educated knowledge blends with innate knowledge in what forms the tacit experience of each individual. Unlike educated knowledge, innate knowledge cannot be forgotten.

3.4 Factors for gesture knowledge transfer

In the following, we rely on Dey's definition of context [78] to identify pieces of information to characterize users involved in gesture interaction for our specific problem of gesture knowledge transfer. We also adhere to the ontological and architectural foundation of defining context of Coutaz et al. [79], which we employ in the form of the specific formalism of the "context of use" [80] consisting of three classes of entities: *users*, hardware and software *platforms*, and *environments*, i.e., $C = (U, P, E)$. Inspired by [80], we identify four factors for gesture knowledge transfer: users, tasks, sensors, and environments.

1. Users produce gesture commands to interact with a computing system. Fahey and Prusak [81] consider that knowledge is meaningless in the absence of a "knower." As knowledge lies with the individual [4,81], gesture knowledge is internalized differently across individuals. Users possess various motor and cognitive abilities, levels of expertise and skill in how they produce gestures, and amount of experience with gesture technology [77,82–85]. Also, cultural aspects [86] favor or constrain the type of gestures that are acceptable in a specific community, and how and when those gestures may be performed [31,32,87]. All these aspects determine differences in how gestures are produced by different users and, therefore, determine differences in how gestures look like for gesture recognizers. For instance, age affects gesture production, e.g., elderly users produce gestures differently than young people [82,85]; children are less precise and take more time to produce touch gestures than adults [77,88]; blind users have different preferences of touch gestures than sighted users [83]; people with low vision produce stroke gestures with different geometric and kinematic characteristics than people without visual impairments [89,90]; users with motor impairments create more complex touch patterns when selecting targets on multi-touch surfaces [84]; etc. Also, previous work has reported many sources of variation for gesture articulation, such as the number of strokes, number of fingers, and number of hands for multi-touch multi-stroke gestures [26,27,91,92]. The complexity of a gesture, objectively assessed with the complexity of its shape geometry [93], has been examined from the users' perspective, and previous work has highlighted strong relationships with production time [91,94], the influence of cognitive load on the appearance of pen gestures [95], as well as the influence of widget representation complexity on user performance for sketch-based interfaces [96]. Also, gesture elicitation studies highlighted that different users have different preferences for gestures to execute various tasks [11,12,14,25,97,98]. Because of these differences, transfer of gesture knowledge *between users* or *between user groups* needs to be addressed at both the recognizer and application levels by designing gesture sets that match functions well and by considering recognition techniques best adapted to classify those gestures accurately.

2. Tasks or activities in which users engage. The gesture command that executes a task can vary according to the designer of the application or the users' preferences. For instance, many symbolic gestures may be designed to effect the "help" function, such as drawing a question mark, drawing letter "H", etc., and different users will manifest different preferences to employ one or another [12,14,25]. To mention just one relevant example, Vatavu and Zaiţi [12] observed fourteen distinct proposals for the gesture to turn up the volume on the TV, including cultural gestures (p. 138). The literature has reported agreement rates between users' gesture preferences between .100 and .400 on the unit scale [24]. Good fit between gestures and the functions they execute makes users believe that the mapping is appropriate and helps them form mental models to explain why the mapping is appropriate [12,25,99].

3. Sensors. A variety of sensors exists today to collect gesture input; see [17–20] for surveys of gesture acquisition in various gesture application domains. Different sensors deliver different representations for the same gesture. For instance, consider a user touching the surface of an interactive table. A basic representation of that gesture consists in the (x, y) coordinates of the touch point at finger lift off. A more detailed representation would include touch pressure, the area of the touch, and the axes of the ellipse produced by the user's finger touching the surface. The same gesture is captured as a series of acceleration points by the accelerometer embedded in the user's smartwatch. An electromyography sensor attached to the user's arm would produce a description of the same gesture in terms of the magnitude of arm muscles' contractions. Finally, a camera-based sensor installed in the environment would have an overall view of the user's whole-body movement as a series of body postures. The type of sensor depends on the application and some applications rely on multiple sensors [100]. Because of these differences in gesture representation, transfer of gesture knowledge *between sensors* needs specific design, careful analysis of the application transfer process and of the mathematical equivalence of gesture representations.

4. Environments represented by social relationships with other individuals present in the same physical settings. Gesture production in public spaces depends on location and audience [31,32], the social acceptance of gestures is influenced by culture, time, and the type of interaction [33], and people are concerned about other people's reactions and acceptance [87]. Cultural gestures also fall into this category [86]. However, where accepted, they represent strong candidates for gesture commands, as they do not require learning or training. Because of such aspects, transfer of interactive gesture knowledge in a social context may be limited to a small range of gesture types.

The above factors, representing instances of the constituting elements of the context of use [80], are key for characterizing gesture knowledge transfer taking place from one user to another, from one sensing device to another, across tasks, and even across environments. Each change in the context of use can be reduced to one or more factors that influence gesture production. Next, we rely on these factors to introduce a new space for characterizing transfer of gesture knowledge.

4 AIS: a space for gesture knowledge transfer

We introduce in this section a new tool for characterizing gesture knowledge transfer which we present in the form of a new representation space for gesture knowledge with three dimensions: *articulation*, *sensing*, and *interpretation*; see Fig. 2. We inform the type of these dimensions from our previous examination of the ways in which gesture knowledge can be transfered in relation to our four factors: users, tasks, sensors, and environments. In the following, we discuss and exemplify each dimension highlighting connections with the factors relevant for gesture knowledge transfer. The next section exemplifies how gesture knowledge transfer can be characterized with the AIS space for practical gesture interaction scenarios (Table 1).

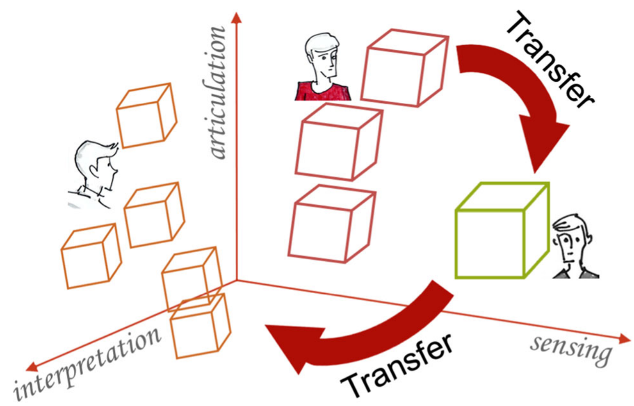

Fig. 2 The AIS space for gesture knowledge transfer is organized along the articulation, interpretation, and sensing dimensions. Regions in this space (visualized as sets of cuboids in *this figure*) represent users' *IUES boxes* of gesture knowledge. Transfer of gesture knowledge represents a transition between two points in the AIS space

1. The articulation dimension registers the ways in which users articulate gestures by connecting to the Users factor of gesture knowledge transfer discussed in the previous section. Gestures can be produced in many ways, and how a gesture is articulated depends on the users' cultural contexts, motor abilities, and cognitive representations. For example, there are 442 distinct ways to produce a simple square with touch input [101] (p. 273). The number of possibilities increases considerably for multi-touch input, for which multiple fingers and two hands can be used to draw the shape of the square [28] (p. 201). The articulation dimension captures the act of users instantiating their goals into a specific gesture (which represents the semantic distance of Hutchins et al. [103]) as well as articulating the specific geometric and kinematic details of those gestures into a motor action (i.e., the articulatory distance of Hutchins et al. [103]). Specifically, the difference in gesture articulation can be appreciated as the difference in the number of strokes or the orientation of strokes between two multi-stroke gestures as in [26], between the number of fingers or hands producing a multi-touch gesture [91], or between specific hand poses employed by users during articulation [11,14,25,97,102]. Gesture similarity or dissimilarity along the articulation space can also be quantified using a distance function, such as those employed by gesture recognizers [28,34,101,104].

Table 1 Examples of gesture knowledge transfer across the three dimensions of the AIS space: *articulation*, *interpretation*, and *sensing*

Dimension of transfer		Example
1.	**Articulation**, *from one way to produce a gesture to another*	Various ways to articulate gestures within and between users [27,28,101]. Perceptions of gesture difficulty favor quick gestures [91,94]. Various factors affect gesture articulation [84,89,90,95,96]
2.	**Sensing**, *from one acquisition sensor to another*	Different sensors register and represent the same gesture differently, e.g., tapping the touch-screen of a smartwatch is represented differently by the smartwatch and the built-in motion sensor
3.	**Interpretation**, *from one interpretation to another*	Various interpretations for the same gesture type and various preferences for gesture-to-function mappings [11,14,15,25,97,102]

2. The sensing dimension registers the ways in which various sensors capture gesture input. Different sensors have different capabilities to register human movement during gesture articulation. For example, a tap on a touch surface can be captured as a 2D point by the touchscreen, as accelerated motion by the user's smartwatch [105], or as electromuscular activity by an electromyography sensor attached to the arm [106]. Which representation makes sense for a particular interaction context depends on the actual application. This dimension connects directly to the Sensors factor of gesture knowledge transfer; see the previous section.

3. The interpretation dimension registers the various interpretations that a particular gesture may have for users. The gesture elicitation literature reported that users manifest different preferences for the gestures to execute a given task [11,12,14,25] and also that users prefer different gestures than those created by experienced designers [102]. Consequently, interpretation may vary according to the Tasks to perform and the Environments in which those tasks are considered.

Individual gesture knowledge is represented in the AIS space as a set of subregions of this space (IUES boxes), represented simplistically as cuboids in Fig. 2. An individual's experience with gesture user interfaces and interactive environments may be represented with IUES boxes of various sizes, i.e., information, understanding, experience, and skill that cover less or more of the dimensions of the AIS space. The social gesture knowledge represents the union of all the IUES boxes. For instance, all the ten cuboids represented in Fig. 2 form the social knowledge of the three depicted users. In this context, gesture knowledge transfer can be represented as "movement" in the AIS space, as follows:

1. Transferring gesture knowledge along the articulation dimension denotes a system able to recognize variations of the same gesture. Various approaches are available to attain such a desideratum. For instance, the $P gesture recognizer [90,101] employs gesture representations that are invariant to articulation details; the RATA. Gesture approach [107] relies on data mining analysis to create new recognizers; optimization algorithms can perform selection of gesture prototypes for template-based recognition [108]; and gesture synthesis techniques enable generation of large training sets [89,104,109].
2. Transferring gesture knowledge along the sensing dimension denotes an environment capable of recognizing gestures that use representations different from those available during training; e.g., a "circle" produced in mid-air in the vertical plane in front of the user would still be correctly recognized, even though the training examples are only available from that user's touch input on the smartphone.
3. Transferring gesture knowledge along the interpretation dimension refers to an environment that can adapt to its users' gesture preferences; e.g., the same "circle" gesture executed by two users in the same environment produces different outcomes, according to each user's preferred mapping between gestures and application functions. The nomadic gestures concept [34] is a step in this direction.

We briefly note here how the articulation, sensing, and interpretation dimensions of the AIS space connect to the three functionalities of gestures illustrated by Cadoz [54]. According to Cadoz, *semiotic* gestures produce meaningful informational messages for the environment as the result of commonly shared cultural experience; *epistemic* gestures offer information that reveals the environment through perception; and *ergotic* gestures act directly on the environment by altering its form and properties. In the AIS space, gesture knowledge instantiates in practical forms of articulations that, once sensed by the environment, require semiotic interpretation to cause actionable effects, i.e., command execution to control the functions and services of the smart environment.

The AIS space has the primarily function to characterize gesture knowledge for specific users or user groups across various application domains and interactive environments, i.e., the AIS space possess *descriptive power*. However, it also has *generative power* by informing on areas that could be exploited further, inviting researchers to explore novel directions. For instance, preliminary studies might show that their users execute gestures in many different ways along the articulation dimension of the AIS space with the net result being large recognition errors caused by the inability of the recognizer to discriminate between various ways to execute the same gesture. Therefore, redesign of the interface could include gesture hints for users, such as starting points for stroke input [110] or setting in place a gesture guidance system [63,73,111]. In the next section, we discuss a real-world example in which we quantify users' variations in gesture articulation. The *comparative power* of the AIS space, although not supported directly at this moment, is nevertheless a consequence of its descriptive power. For example, plotting the articulation details of two gesture sets for the same application can reveal differences in the ways users associate gesture types and meaning. Depending on the designer's goal, several actions can be taken, such as considering multiple gestures for the same command [27,112], redesigning the gesture set [25,102], and even reconsider gesture metaphors [113,114]. The second example that we discuss next in the paper examines the transfer of gesture knowledge on the *interpretation* × *sensing* dimensions.

5 Case studies for gesture knowledge transfer

We exemplify in this section the use of the AIS space with two practical case studies. In the first study, we examine pen gestures on the *articulation* axis. In the second case study, we analyze users' mid-air gesture preferences on the *interpretation* × *sensing* axis for gesture control of the TV set.

5.1 Gesture transfer on the *articulation* dimension: a case study for pen gestures

To analyze gesture knowledge transfer on the articulation axis, we computed the consensus between users' articulations of stroke input for a large dataset consisting of 14,005 symbols produced by 34 subjects for 14 distinct symbol types: accident, bomb, car, casualty, electricity, fire, fire brigade, flood, gas, injury, paramedics, person, police, and roadblock [115]. Following the methodology of Anthony et al. [26], we quantified consensus between gesture executions with real numbers in the [0, 1] interval. Consensus levels can be interpreted as the percentage of pairs of gestures that are similar in their articulation details (i.e., the number of strokes, stroke orientation, and direction); see [24].

We found that the average consensus was .785 within users ($SD = .135$) and .368 between users ($SD = .274$); see Fig. 3. A Wilcoxon signed-rank test showed that the difference between these levels of consensus was statistically significant ($Z = -3.296$, $p < .001$) with a large effect size ($r = .623$).

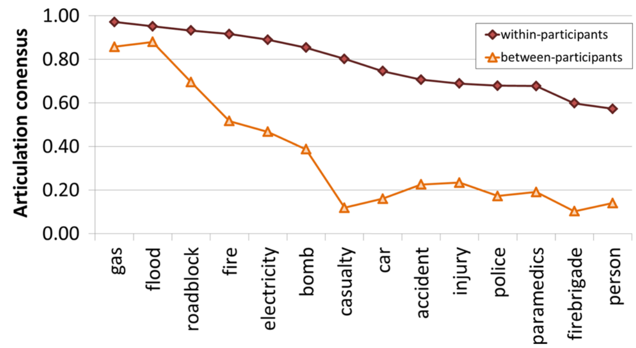

Fig. 3 Articulation consensus (expressed on the unit scale) for the NicIcon symbols of Willems et al. [115]. *Notes* consensus values were computed from 14,005 gesture samples; both within- and between-users consensus is reported

Different gesture types determined different levels of consensus. For instance, participants were more consistent for some gestures (e.g., "gas" or "flood", which scored .972 and .951 within-subject consensus) than for others (e.g., "firebridge" or "person" with .598 and .573 consensus, respectively). The between-users consensus was two times smaller, yet values were significantly correlated at the level of individual gesture types (Pearson's $r_{(N=14)} = .876$, $p < .01$). The explanation of these findings can be found in each individual's IUES gesture knowledge box. In this case, *skill* helps users produce symbols efficiently (e.g., producing gestures in the same way maximizes execution speed), which usually results from automatisms created through *experience*. Still, for some gesture types, even within-user consensus is low (e.g., less than .600 for the "person" symbol), which suggests that such automatisms still need to be formed for unfamiliar symbols.

To support articulation invariance, applications should implement gesture knowledge transfer in the *articulation* dimension. This means recognizing gestures no matter how users produce them. At this moment, the \$P point-cloud gesture recognizer [90,101] is the only approach meeting that desideratum. Figure 5 shows the recognition rates delivered by the \$P recognizer for both user-dependent (92.5% accuracy) and user-independent (75.6%) training conditions.[1]

The various levels of *experience* that users have acquired over time and the *understanding* that they formed about the task (e.g., how to perform the "car" symbol more efficiently, for example) explain the low consensus between users. For instance, we found 39 distinct ways in which participants produced the "car" symbol from 1010 executions [115]. The IUES boxes for this symbol are illustrated for all the 33 participants as dots in AIS space of this case study shown in Fig. 4. Please note that because of the nominal nature of the artic-

[1] Training and testing procedures were conducted according to Vatavu et al. [101] by varying the number of training samples per gesture type from 1 to 8 and the number of training participants from 1 to 8.

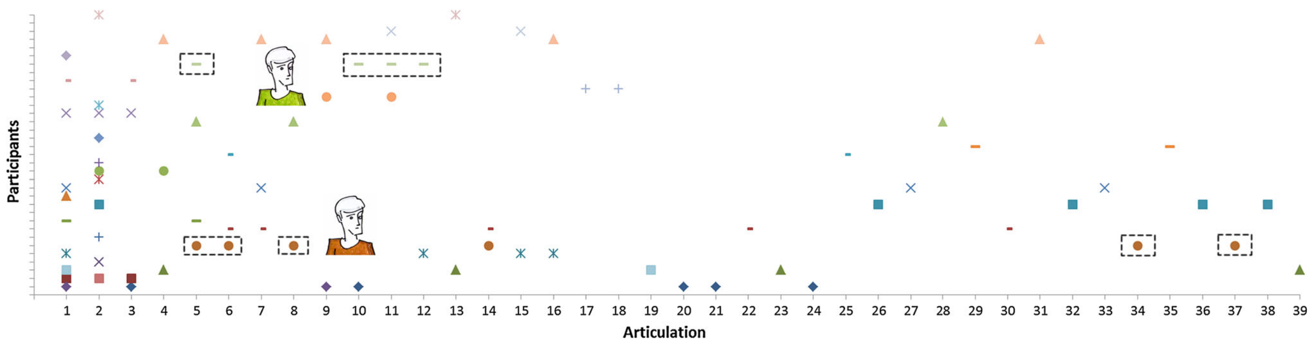

Fig. 4 IUES boxes (represented as *dots*) for the articulation dimension of the AIS space showing the variation of the "*car*" symbol [115]. *Notes* participants (1–33) are shown on the vertical axis; the IUES boxes for two participants' are highlighted

ulation dimension, IUES boxes are reduced to dots in this visualization and, consequently, the AIS space is discrete. In this space, a color dot marks a specific articulation of the "car" symbol produced by a specific user; see the highlighted boxes representative of two users' articulations in Fig. 4. When users are consistent in their gesture articulations, few boxes exist, whereas larger variation in articulation produces multiple boxes.

Transfer of gesture knowledge for the "car" symbol can take place both at the user level and between users. For example, a user may switch between different articulations over time or may use different articulations of the same gesture type to accommodate various devices, such as using more or less strokes depending on the available area to draw, e.g., smartwatch versus tablet. Such a transfer (*within*-user) can be visualized along the horizontal dimension of Fig. 4, where multiple symbols and colors encode various ways to articulate the "car" symbol. Transfer of gesture knowledge can also take place *between* users that share knowledge directly or indirectly by cooperating in the same task. Different users can thus reach consensus over their gesture articulation patterns for reasons of task productivity or they can adopt each others' ways to articulate gestures for articulation effectiveness and efficiency. In that case, transfer of gesture knowledge occurs between users and is visualized along the vertical dimension of Fig. 4.

5.2 Gesture transfer on the *interpretation* × *sensing* dimensions: a case study for mid-air gestures

We continue with a case study regarding users' subjective *interpretations* of gesture commands in two gesture *sensing* contexts. Therefore, we perform gesture analysis along the *interpretation* × *sensing* dimensions of the AIS space. Twenty (20) participants (mean age 27.4 years, $SD = 7.4$) were elicited for preferences of gesture commands to control various functions on a TV screen (play, pause, go to next item, go to previous item, open menu, hide menu, and ask for system help) by following the gesture elicitation methodol-

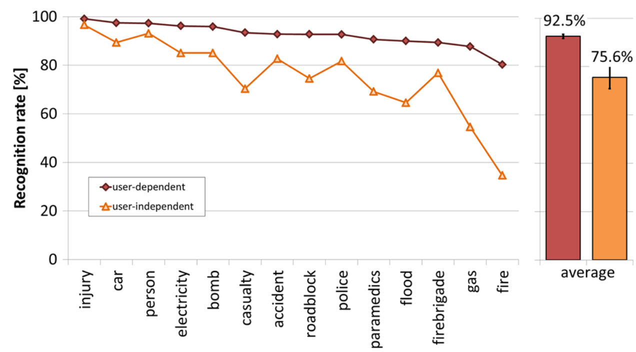

Fig. 5 Recognition rates delivered by the $P recognizer [101] for the NicIcon symbols [115]. *Notes* gestures are ordered according to the user-dependent recognition rate; both user-dependent and user-independent rates are reported

ogy [24,25]. Participants proposed gestures in two different acquisition scenarios: using a motion-sensing remote controller and performing mid-air gestures in front of a Microsoft Kinect sensor. Agreement rate analysis was conducted using the AGATe toolkit [24,99].

Participants' gesture proposals represent instances of their IUES boxes of gesture knowledge applied for the specific TV interaction scenario. The *sensing* dimension of the AIS space implements two values corresponding to the motion-sensing controller and the free-hand gesture acquisition conditions. The *interpretation* dimension of AIS implements seven values, one for each function to execute on the TV set. In the following, we are interested in the transfer of gesture knowledge that takes place on these two axes (Figs. 5, 6).

To understand gesture knowledge transfer across the *interpretation* axis, we computed agreement rates using the formula of Vatavu and Wobbrock [24] (p. 1327). The average agreement was .373 for the motion-sensing controller and .307 for the free-hand scenario; see Fig. 7, left. These values can be interpreted as medium to high agreement, according to the recommendations of [24] (p. 1332). A Pearson test showed a significant correlation between the agreement rates reached for gestures under the two sensing conditions

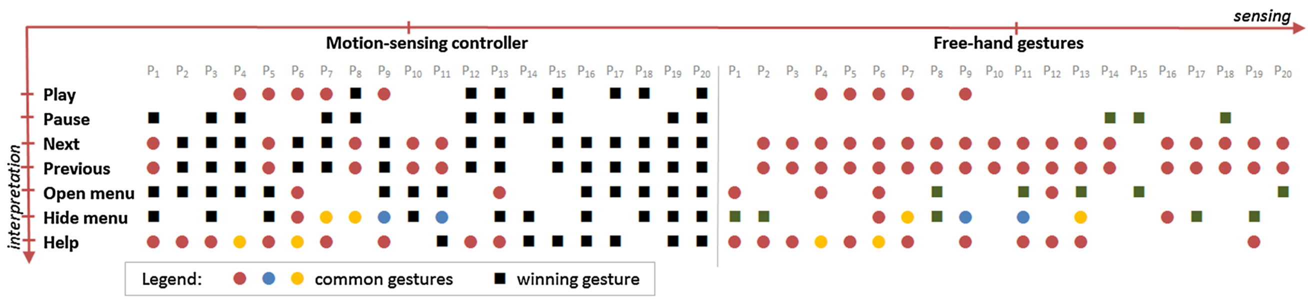

Fig. 6 Gesture preferences of 20 users, 7 tasks, and 2 sensors. Circles show common preferences for the same interpretation, e.g., 5 participants have the same preference for "Play". Squares show the winning gesture for each function

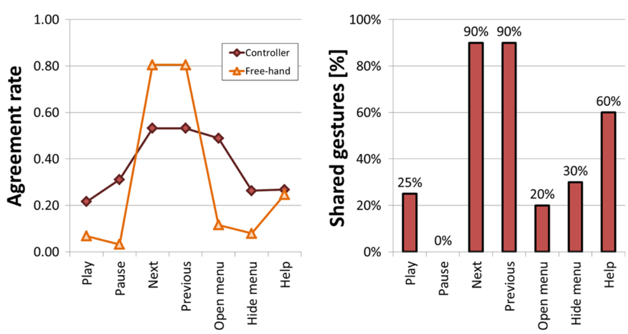

Fig. 7 *Left* agreement rates for gestures elicited in the two gesture acquisition scenarios (controller and free-hand); *right* percentage of shared gestures

($r_{(N=6)} = .769$, $p < .05$). More agreement (+21.5%) was measured for the remote controller, probably because of its form factor that looked familiar to the participants, enabling them to reuse their experience in controlling the TV using a remote. Nevertheless, all agreement rates were significantly greater than zero ($p < .05$), as indicated by V_{rd} tests [24]. We also found a significant effect of function type over agreement rate for both sensing scenarios ($V_{rd}(6) = 97.599$ and $V_{rd}(6) = 612.450$, respectively, $p < .001$), which shows that the specifics of each function made participants think of different gestures.

To understand gesture knowledge transfer across the *sensing* axis, we looked at how many times participants proposed the same gesture for a given function for both sensing conditions. The percentage of shared gestures varied between 0% (for "Pause") and 90% (for "Next" and "Previous"), with an average percent of 45%. This result shows that participants were inclined to reuse the gesture knowledge they had just gained for the other gesture sensing condition; see Fig. 7, right. Figure 6 illustrates the main results visually. Instead of listing actual gesture proposals, we focus on representing gestures that are common across participants and across sensors. For instance, participants P_4, P_5, P_6, P_7, and P_9 proposed the same gesture for "Play" in both sensing scenarios. Different colors for circles indicate different gesture types. We used squares to show the winning gesture for each scenario, i.e., the gesture for which the most participants agreed on. Although each participant proposed a gesture for each function, for clarity purposes we omitted from Fig. 6 those proposals that did not match with others.

We conclude that participants reused their gesture *experience* from one domain in order to start off with a reasonable level of *skill* and *experience* in a different gesture *sensing* scenario, according to their generic *information* about gesture interfaces and the *understanding* they formed about the task. This type of transfer can be visualized along the horizontal axis of Fig. 6. To support various sensors, an application should implement gesture knowledge transfer in the sensing dimension. This means designing algorithms that can recognize gestures independently of their representation. Gesture transfer can also take place along the *interpretation* dimension (vertical axis in Fig. 6) when users employ the same gesture type to execute multiple functions according to the current context of use, or they adopt other users' associations between gestures and functions. To support various gesture to function mappings, an application should implement gesture transfer in the interpretation dimension by adaptively matching users' gesture preferences to the tasks they execute. The result will be higher flexibility by leveraging existing knowledge for new contexts of use.

6 Conclusion

We introduced in this work the concept of interactive gestures as knowledge to address the problem of gesture knowledge transfer across multiple contexts of use. While this work represents the first step toward understanding gesture knowledge transfer, it already provides the community with several contributions: a taxonomy of gesture knowledge, the IUES box concept to describe the various dimensions of gesture knowledge at the level of the individual, and the AIS space to characterize gesture knowledge transfer. Future work will consider extending these results towards deriving a formal, mathematical definition of the IUES and AIS construct, possibly including various channels of users' motor and cognitive abilities. Due to the importance of gesture interactions for smart environments, we believe that the topic of gesture knowledge transfer will receive considerable scholarly attention in the future, and we are eager to see how our results will be used by the community to develop a comprehensive theory of gesture knowledge, unveil new gesture discoveries, and inform gesture interface design for new environments.

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