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ORIGINAL RESEARCH

Flexible gesture input with radars: systematic literature review and taxonomy of radar sensing integration in ambient intelligence environments

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Abstract
We examine radar-based gesture input for interactive computer systems, a technology that has recently grown in terms of commercial availability, affordability, and popularity among researchers and practitioners, where radar sensors are leveraged to detect user input performed in mid-air, on the body, and around physical objects and digital devices. We analyze forty-five academic papers published on this topic between 2010 and 2021, and report results regarding gesture recognition techniques, application types, and evaluation approaches for radar-based gesture input. Our findings reveal that (1) deep learning techniques, such as Convolutional Neural Networks, have been the most popular approach for radar-based gesture recognition, (2) application opportunities for implementing radar gestures have been diverse, but without any clear contender for a game changer in this area, and (3) the gesture sets employed in prior work have been small with a median of just six gesture types. Based on these findings, we draw ten implications for integrating radar-based gesture sensing in ambient intelligence environments.

Keywords Gesture input · Radar sensing · Gesture recognition · Ambient intelligence · Smart environments · Interactive computer systems · interactive environments

1 Introduction

Gesture-based input for smart environments enables users to leverage body pose and movement for more efficient, fluent, and expressive interactions. Gesture types used for interactive purposes range from symbolic stroke gestures commonly employed on mobile devices (Magrofuoco et al 2021) to finger, hand, and arm movements sensed with wearables (Gheran et al 2018), mid-air gestures for interacting with content visualized on ambient displays (Ardito et al 2015), foot-based interaction (Velloso et al 2015), and whole-body gestures (Vatavu 2017a). To sense and recognize users' gesture input, computer systems leverage (i) *sensors,* e.g., accelerometers integrated in electronic rings (Gheran et al 2018), (ii) *recognition algorithms,* e.g., Nearest-Neighbor classification of whole-body movement with the Dynamic Time Warping dissimilarity function (Vatavu 2017b), and (iii) *gesture sets* for specifying mappings between gestures and system functions, such as drawing the letter "M" in mid-air to display a contextual menu on the smart TV (Vatavu 2012). Among the sensors that detect contactless gestures, radars enable unique opportunities for interactive computer systems and smart environments, from simple presence and proximity detection to microgestures performed at finger level (Lien et al 2016), on-body input (Leiva et al 2020), tangible interaction involving physical objects (Attygalle et al 2021), and through-the-wall detection of movement (Adib et al 2015); see Fig. 1 for a few

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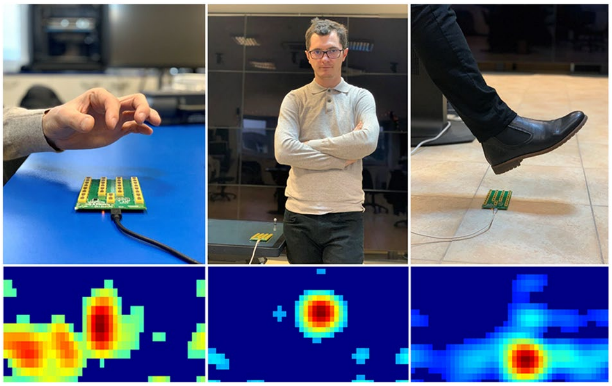

Fig. 1 The versatility of radars to sense a wide variety of gesture types: gestures of the hand and fingers (top left), proximity sensing (top middle), and gestures of the feet (top right). At the bottom, 2D representations are shown for these gestures, reported by the Walabot radar. Also note the versatility of possible placement of radars in the environment, an aspect that we examine in detail in Sect. 6

examples of such gesture types together with their signal representations acquired using an off-the-shelf radar device.

Radar-based gesture recognition has recently received increased attention (Palipana et al 2021; Sluÿters et al 2022; Ahmed et al 2021; Yeo and Quigley 2017) at the intersection of the scientific communities of Machine Learning (ML) and Human-Computer Interaction (HCI) due to the application potential of radars to enable interactions via unrestricted body movement and contactless gestures; see Ahmed et al (2021) for a survey of radar technology for the representation and recognition of hand gestures. Besides hand gestures, however, the versatility of radars makes them effective at sensing body gestures of many types, some of which are illustrated in Fig. 1, but less addressed in the scientific community compared to hand gesture input. Additionally, key aspects for the effective implementation of radar-based gesture input, such as gesture set design and methods to evaluate user performance with radar gestures, have been little examined compared to the extensive research conducted in the scientific literature on other gesture types, such as ring gestures (Vatavu and Bilius 2021), touchscreen stroke gestures (Magrofuoco et al 2021), multitouch gestures (Cirelli and Nakamura 2014), or foot-based interactions (Velloso et al 2015). In this context, our contributions are as follows:

1. We present the results of a Systematic Literature Review (SLR) conducted to structure and analyze gesture-based sensing and recognition with radar devices for interactive computer systems and environments. Unlike other types of reviews, SLRs are methodical, comprehensive, transparent, and replicable (Siddaway et al 2019).
2. Based on the results of our SLR, we propose ten implications and future work directions for the research and practice of interactive computer systems and smart environments implementing radar-based gesture sensing and recognition. We also present a dictionary of radar gestures compiled from an analysis of 307 individual gestures extracted from 45 scientific papers on this topic.
3. To foster further research on and applications of radar-based gesture input in Ambient Intelligence (AmI) applications, we propose a five-category taxonomy of possible locations from the physical environment where radars can be installed, attached to, or integrated.

Our contributions are intended to provide the scientific community with a practical means to inform design of contactless gesture input detected with a versatile sensing technology that matches the quality characteristics of interacting in AmI environments (Cook et al 2009). Next, we specify the scope of our work and outline our research questions for radar gestures used for interactive systems and environments.

2 Context, scope, and research questions

The operating principle of radar sensing is represented by the emission and reception of electromagnetic waves. After hitting a target, the emitted radiation is spread, of which a part returns to the radar, where it is caught by the receiver. The properties of the received signal, such as the frequency, amplitude, and delay, provide key information about the target's shape and orientation, but also about the distance and speed relative to the radar. Therefore, radar-based sensing of contactless gestures can reveal a wealth of information that computer systems can leverage for implementing user interactions. Although radars have been an active area of scientific research (Li et al 2017; Skolnik 2008), the use of radar technology for interacting with computer systems has been rather limited in scope because of the large form factors of radar devices, their high energy consumption, and large computing resources needed for processing radar signals. However, recent advances in machine learning techniques coupled with computer miniaturization have rendered radars practical for integration into consumer devices, one relevant example being the Google Pixel 4 smartphone with Soli (Lien et al 2016). In this context, new opportunities arise for interactive computer systems and smart environments that can leverage radar sensing to detect the position and movement of the user's body. Before proceeding further, we provide our operational definition of a radar gesture:

> ***Definition:*** A radar gesture is any movement or pose of a body part or the whole body, performed in mid-air, around a physical object or digital device, or in relation

to the body, object, or device, which is detectable and recognizable by a radar sensor.

This definition is broad enough to cover a variety of gestures, from finger and hand poses to mid-air movements of the hands and arms to gestures performed with the whole body, but also gestures that involve physical objects, surfaces, and digital devices from the environment (Adib et al 2015; Attygalle et al 2021; Avrahami et al 2019; Leiva et al 2020). For example, Avrahami et al (2019) used RF radars to recognize user activity on work surfaces. Thus, radars enable a variety of gesture input, which we scrutinize in our SLR to complement the survey of Ahmed et al (2021) on hand gestures. Moreover, while Ahmed et al (2021) focused on technical aspects of gesture sensing and recognition, such as acquisition technology (pulsed vs. continuous-wave radars), signal representation (time-amplitude, time-Doppler, range-amplitude), and recognition algorithms for specific gesture representations computed from radar signals, we provide a complementary perspective. Our focus is on gesture set design and taxonomy of locations from the environment where to install radars. This focus requires an operational definition of a smart environment, for which we adopt the perspective of Cook and Das (2004), i.e., "a small world where all kinds of smart devices are continuously working to make inhabitants' lives more comfortable" (p. 3), and of Weiser et al (1999) of a "physical world richly and invisibly interwoven with sensors, actuators, displays, and computational elements, embedded seamlessly in the everyday objects of our lives and connected through a continuous network" (p. 694). This shift of perspective, centered on smart environments from the AmI vision of computing, enables us to report new results and draw implications for practical applications of radars. We address three research questions:

RQ$_1$: What types of gestures have been examined in the scientific literature on radar-based gesture interaction?

RQ$_2$: In what ways has gesture set design been influenced by the characteristics of radar gesture recognition techniques and applications of radar gestures?

RQ$_3$: Where have radars been placed/installed in the physical environment to sense user gestures?

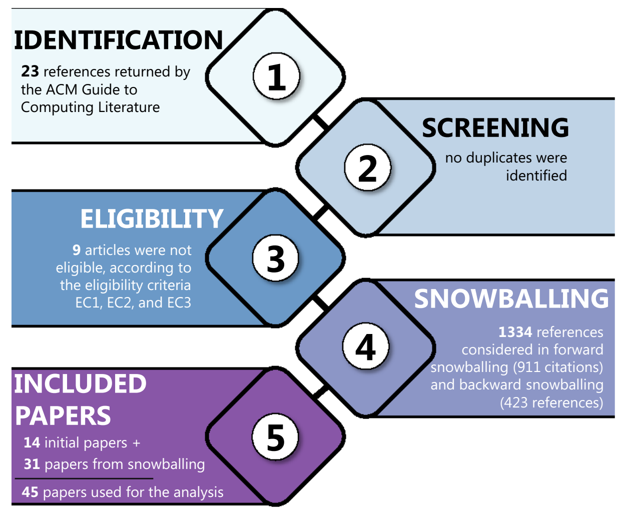

Fig. 2 The results of the *identification*, *screening*, *eligibility*, *snowballing*, and *inclusion* stages of our SLR study

3 Study design

To answer our research questions, we conducted a SLR, for which we employed the Best Practice Guide of Siddaway et al (2019), and implemented *identification, screening, eligibility, snowballing*, and *inclusion* stages. Figure 2 presents the results obtained after each stage, illustrated using the PRISMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses) diagram (Liberati et al 2009).

During the *identification* stage, we searched for scientific papers relevant to our scope by using the keywords "gesture" and "radar" with the following query: "Abstract: (radar AND gesture*)." We ran the query in the ACM Guide to Computing Literature,[1] the most comprehensive bibliographic database focused exclusively on the field of computing with about three million records from many publishers. The query returned a total of 23 bibliographic results. During the *screening* stage, we read the abstracts to determine their relevance to our scope. During the *eligibility* stage, we read each paper and used the following criteria to filter out results not relevant, either in form or content, to using radar gestures for interactive systems:

EC$_1$: *The paper is academic* and underwent peer review. Magazine articles, white papers, and tutorials were excluded. For example, we excluded Helal et al (2013) and Townley (2018).

[1] https://libraries.acm.org/digital-library/acm-guide-to-computing-literature

EC_2: *The paper is about radars used for interactive systems.* We excluded four papers (Goenetxea et al 2010; Liu et al 2019; Reski et al 2020; van Dantzich et al 2002) that did not address interactions enabled by radars, e.g., van Dantzich et al (2002) presented a user interface with a radar-like visualization.

EC_3: *The paper is about gesture-based interaction.* We excluded three papers (Shaker et al 2018; Shui et al 2009; Zhang et al 2017) that did not present gestures.

We used these eligibility criteria to identify peer-reviewed scientific contributions about radar-based gestures for interactive systems, according to our scope presented in Sect. 2. After the eligibility stage, we arrived at a number of 14 relevant papers, for which we applied two snowballing procedures (Wohlin 2014): (1) *backward snowballing,* where we analyzed the references of all of the eligible papers, total of 423, and (2) *forward snowballing,* where we analyzed their Google Scholar citations, total of 911. Following the *snowballing* stage, we identified 31 additional papers that met our three eligibility criteria. Our final set of papers contains 45 academic papers published between 2010 and 2021, of which 27 from IEEE Xplore,[2] 10 from ACM DL,[3] and 8 from other publishers. These papers were analyzed by two researchers (the first two authors of this article), who extracted the following information to address our research questions:

1. Information about *gesture technology:* (i) recognition techniques, (ii) placement and installation of the radars in the environment, (iii) gesture types, and (iv) mappings between gestures and system functions. We used this information to address RQ_1 and RQ_3.
2. Information about *application types* for radar-based gesture interaction. A total of 17 application categories emerged from our analysis, e.g., video games (Iwamoto et al 2010), in-vehicle interaction (Sun et al 2018), assistive technology (Li et al 2015), etc.; details follow in Sect. 4. We used this information to address RQ_2.
3. Information about the *validation of the scientific and technical contributions,* with three categories: (i) *system performance*, e.g., recognition accuracy rate or recognition time, (ii) *demonstration*, e.g., working prototype, application, or use case for radar gestures, and (iii) *user study*, i.e., studies for radar gesture interaction involving representative end users. We used this information to complement our findings in relation to RQ_1 to RQ_3.

[2] https://ieeexplore.ieee.org/Xplore/home.jsp

[3] https://dl.acm.org

4 Results

We present a meta-analysis of 45 scientific papers on radar gestures for interactive computer systems and environments.

4.1 Gesture recognition techniques

Figure 3, top presents an overview of the recognition techniques for radar gestures that we identified in the scientific literature, shown in descending order of their frequency. The most frequently used technique was represented by Convolutional Neural Networks (CNNs), used in 32.89% of the papers analyzed in our SLR. Other techniques included k-Nearest Neighbors (kNN), and Long Short-Term Memory (LSTM) with 18.42% and 14.47%. For example, Sakamoto et al (2017) reported the recognition accuracy of a CNN trained to recognize a set of three gestures, Zhang et al (2020b) employed a kNN with a set of six gestures for robot control, and Zheng et al (2021) employed a LSTM for a set of eight gestures for in-vehicle input. Other recognition techniques were used sporadically, such as Self-Organizing Maps (SOM) (Patra et al 2018), Linear Discriminant Analysis (LDA) (Bannon et al 2020), Quadratic Discriminant Analysis (QDA) (Bannon et al 2020) and Support-Vector Machines (SVMs) (Gigie et al 2019). The most common choices for radar sensing frequencies were 60 GHz and 24 GHz, identified in 58% of the papers from our SLR. For example, Dekker et al (2017) employed a FMCW radar operating in the 24 GHz ISM frequency band with an effective isotropic radiated power level of 0 dBm, Zhang et al (2018a) used a 24 GHz FMCW, Choi et al (2019) used Soli, a 60 GHz FMCW, and Wang et al (2019b) employed a 4 GHz FMCW radar sensor. The highest frequency was 120 GHz (Altmann et al 2021) and the lowest 2.4 GHz (Molchanov et al 2015; Wan et al 2014; Sakamoto et al 2018, 2017). A percentage of 8.89% of the papers did not specify the working frequency of the radar (Sang et al 2018; Yeo et al 2017; Leiva et al 2020; Iwamoto et al 2010). Overall, our findings indicate a predilection for deep learning approaches for radar-based gesture recognition, likely due to the complexity of radar signals and the corresponding gesture representation, e.g., CNNs are known for their good performance in handling complex signals (Xia et al 2021; Skaria et al 2019; Zhang et al 2018b, 2020a).

4.2 Validation of scientific contributions

We extracted information about the validation of the scientific contributions about radar-based gestures for interactive computer systems and smart environments; see Fig. 3, middle. We found that *system performance* (e.g., recognition accuracy rate, recognition time, etc.) was evaluated in

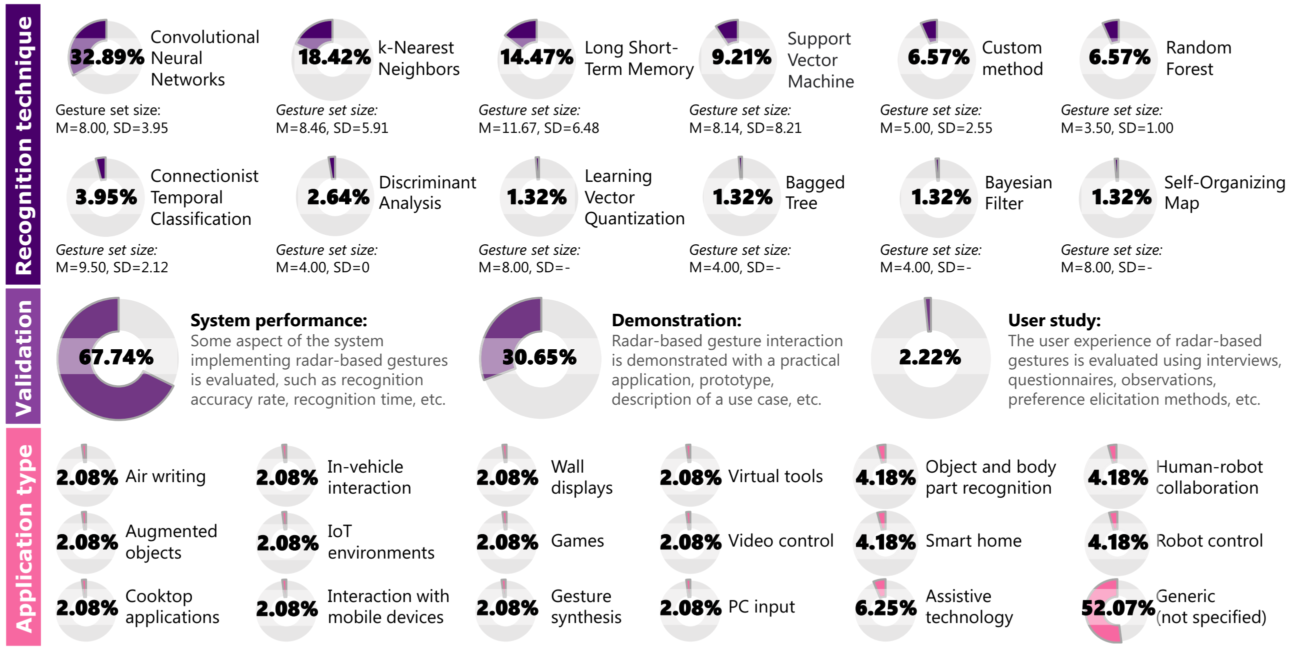

Fig. 3 Gesture recognition techniques, validation types, and application categories for radar gestures identified in our SLR. *Notes:* some of the papers described multiple applications, employed more than one validation type, and evaluated more than one gesture recognition technique. For example, a number of 25 papers of the 76 reported recognition techniques implemented CNNs (25/76=32.89%), and three applications, of the 48 reported, were about assistive technology (3/48=6.25%)

67.74% of the papers analyzed in our SLR. For example, Amin et al (2019) reported recognition accuracy rates and confusion matrix analysis for SVMs, kNNs, and PCA for a set of fifteen hand gestures represented as time-frequency spectrograms. A percent of 30.65% of the papers *demonstrated applications*, which we discuss in detail in the next subsection. For example, Lien et al (2016) introduced the Soli radar to detect gestures at sub-millimeter precision and an interaction language for virtual tools controlled using Soli. We found only one article describing a user study: Liu et al (2020) evaluated aspects of the user experience of a smart home application, e.g., the perceived convenience and fun of using radar-based gestures vs. voice input.

4.3 Application types

Applications of radar gestures were not explicitly stated in 52.07% of the papers that we analyzed in our SLR. For example, Wang et al (2019c) proposed a gesture recognition system that delivered 96.4% recognition accuracy for a set of five gestures (forward, backward, push, pull, and rotate) with the goal of demonstrating noninvasive, real-time human–machine interaction, but did not discuss a specific application. Wang et al (2019a) proposed a gesture recognition technique for Soli, a radar capable to detect a set of eleven gestures with 99.7% user-independent accuracy based on a combination of Convolutional and Recurrent Neural Networks, but did not discuss applications. Most of the papers that presented applications addressed smart homes (Liu et al 2020), IoT environments (Wang et al 2021), assistive technology (Li et al 2015; Santhalingam et al 2020), and robot control (Zhang et al 2020b); see Fig. 3, bottom for an overview of application categories for radar-based gesture interaction. This result shows a diversity of application opportunities, but without a clear trend or killer application, indicating that the scientific community is still exploring potential applications for radar-based interactions.

4.4 Locations of radars

We also extracted information about the locations where radars were installed in the physical environment to sense gestures, e.g., on a table, the user's body, floor, etc. A percent of 42.22% of the papers did not provide any information regarding the physical location or installation of the radar. The rest of the papers (57.78%) reported various locations, as follows: on the floor (Iwamoto et al 2010), integration in the smartphone (Hayashi et al 2021), inside the vehicle (Sun et al 2018), on the body (Li et al 2015), on tripod (Palipana et al 2021; Salami et al 2022; Kern et al 2020), on the wall (Liu et al 2020; Sakamoto et al 2017; Zheng et al 2021); see Fig. 4 for details. In 37.77% of the papers analyzed in our SLR, radars were placed on a table. Two papers (Wang et al

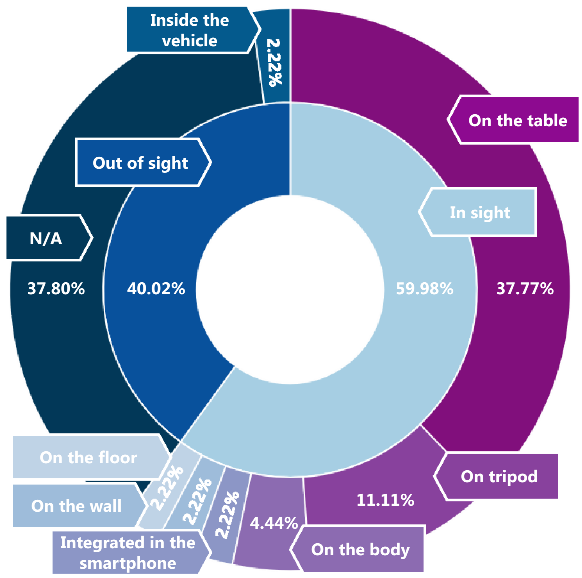

Fig. 4 Overview of physical locations, extracted in our SLR, where radars were placed for sensing gestures

2021; Zhang et al 2020b) used several radars, which were placed on a table as well.

4.5 Gesture types

We extracted a total number of 307 individual gestures performed with the fingers, hands, arms, and the whole body, and clustered them according to their type; see Fig. 5, top. The most frequent gesture was "push," e.g., Palipana et al (2021) implemented "push" for a mid-air input recognition system with potential applications for offices, restaurants, and factory environments. Other frequently used gestures were directional and circular swipes. For example, Hazra and Santra (2019) used a circular movement of the finger performed above the radar sensor with a gesture set designed to minimize muscle movement and hand displacement. Other gestures that we found in more than one paper included "finger rub" (Hazra and Santra 2019, 2018; Wang et al 2016), "grab" (Lee et al 2020; Hazra and Santra 2019, 2018), and "click" (Bannon et al 2020; Wang et al 2020b). Figure 5, bottom illustrates gestures performed with other body parts than the hands. We identified fourteen such gestures, of which seven performed with the tongue (Li et al 2015). Iwamoto et al (2010) employed whole-body gestures, such as "stand on one foot," "stand up," and "squat." Other gestures were designed for the arms, such as "fly" (Kern et al 2020), "rotate clockwise" (Wang et al 2021), and "stop" (Kern et al 2020), and one gesture involved a physical object (a chair) (Sakamoto et al 2018).

Besides the information about gesture types used in prior work, another interesting finding from our analysis regards

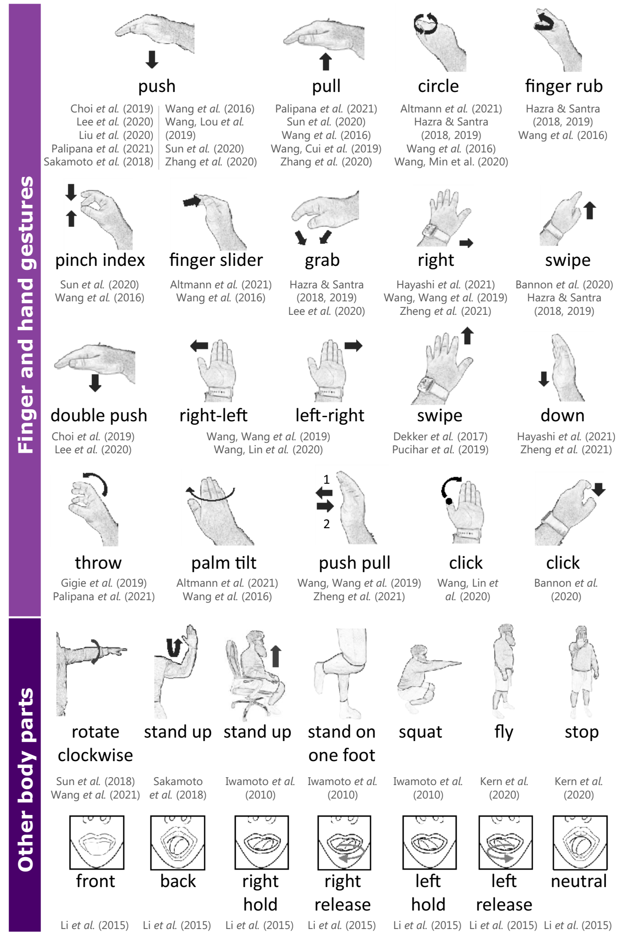

Fig. 5 Finger and hand gestures (top) and gestures performed with other body parts (bottom), identified in our SLR. *Note:* finger and hand gestures were the most common

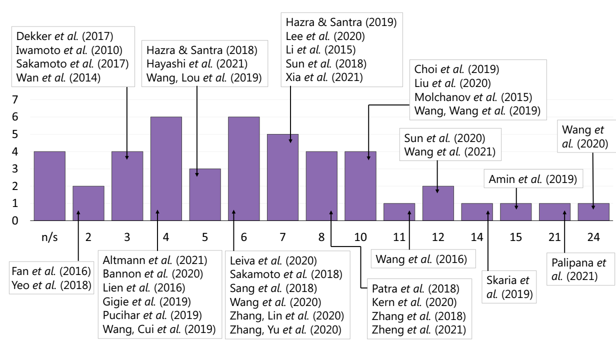

Fig. 6 Histogram of gesture set sizes extracted in our SLR

the size of the gesture sets, which varied from just two gestures (Yeo et al 2018; Fan et al 2016) to a maximum of twenty-four (Wang et al 2020a). The median size of the gesture sets that we analyzed in our SLR was six (M=6.82, SD=4.96); see Fig. 6. This finding indicates that gesture sets have been overall limited for applications involving radars. Next, we present several implications of this finding for interactive computer systems and smart environments.

5 Implications

The results of our SLR showed that the scientific research on radar-based gesture recognition and interaction has been limited compared to other gesture sensing technologies. Also, a diversity of applications have been examined, but we could not identify any conclusive trend or killer application among them. Furthermore, there has been little to no examination of the user experience of radar gestures for interactive computer systems and smart environments, while the large majority of validation types have addressed system performance, e.g., recognition accuracy rates. Based on these findings, we present several implications for radar-based gesture recognition and interaction, which we accompany with future work directions. In Sect. 6, we expand one of our implications to propose a taxonomy of locations to integrate radar sensors in physical environments for new application opportunities.

❶ **More studies are needed to understand end users' preferences, expectations, needs, and behavior regarding radar gestures for interactive computer systems and smart environments.** This direction of scientific investigation includes understanding aspects of learnability and memorability (Nacenta et al 2013), user experience (Xuan et al 2019), and perceived difficulty (Rekik et al 2014) of using radar-based gesture input, but also users' preferences for intuitive associations between radar gestures and system functions (Magrofuoco et al 2019). Expected results will complement those about the system performance of radar gestures (see Sect. 4) towards more usable and effective interactive systems for end users.

❷ **Evaluate the performance of radar gesture recognizers on datasets with more gesture types.** Our results showed a median set size of just six gestures (Fig. 6) with limited utility and expressive power for practical applications. Pantomime (Palipana et al 2021) is one exception with a publicly available dataset containing 21 gesture types and 22,000 templates. In contrast, other types of gesture sensing technologies have employed considerably larger gesture sets, e.g., Kristensson and Zhai (2004) designed a vocabulary of 10k-20k words for gesture shape writing on touchscreens, Appert and Zhai (2009) reported users being able to recall three times as many stroke-gesture commands compared to keyboard shortcuts, and Nacenta et al (2013) found that user-defined multitouch gestures are 44% more memorable for end users than gestures created by designers. An interesting note is that the size of the radar gesture datasets employed by prior work is large, but not in terms of the diversity of the constituent gesture types, but because of the number of gesture samples or templates needed by specialized recognition techniques, e.g., CNNs, to deliver high accuracy rates.

❸ **Examine more diverse radar gesture types, beyond simple directional movements and hand poses.** As Fig. 5, top shows, the most frequent radar-based gestures used in previous work have been very simple, mainly consisting of hand poses and directional swipes. For example, the Pantomime gesture set (Palipana et al 2021) includes the "push" gesture performed in various directions, "lift," "pull," directional swipes, two-hand "throw," "push," "pull," "lateral-raise," and "circle (counter-)clockwise" gestures. According to the hand gesture classification of Aigner et al (2012), the radar gestures depicted in Fig. 5, top are *semaphoric* in nature, while other gestures categories, such as *pantomimic* and *iconic*, have not been covered to the same extent. Also, gestures performed with other body parts (Fig. 5, bottom) have been considered to a less extent (14/307=4.56%) despite the versatility of radar sensors to detect gestures of many types. Thus, we recommend more explorations of radar gestures performed with various body parts, either in isolation or combination. To this end, we point to the SLR of Villarreal-Narvaez et al (2020) for a diversity of gesture types proposed and preferred by end users.

❹ **Identify genuine application areas for radar gestures.** Almost half of the papers analyzed in our SLR did not discuss applications of radar-based gesture recognition and interaction, but only introduced and/or evaluated radar gesture recognizers. In this context, we believe that the killer application for radar gestures is still to be identified. Potential candidates may include using gestures from a distance for interactive systems, e.g., robot control, or gestures performed under occlusion, e.g., under a table, for the smart environments of the AmI vision. Thus, further explorations of the application potential of radar gestures are recommended.

❺ **Design interactive systems that combine multiple radar sensors, but also radars with other sensing technology**. Radars present unique opportunities for sensing presence and proximity, body poses, movement, and gestures. By combining radar gesture sensing with other gesture acquisition technologies, either from the environment (e.g., video cameras, depth sensors) or worn on the body (e.g., smartwatches, smart rings), cross-device input could be leveraged for more expressive and richer gesture interactions. For example, Avrahami et al (2019) found that two orthogonal radars improve recognition accuracy, while a radar and a smartwatch used together enable user identification besides gesture recognition. Such explorations will also impact the development of new gesture recognition techniques that combine data collected from different sensors. Combining multiple radar sensors is also likely to increase the processing complexity of the corresponding signals, which may interfere with each other. Soft sensors, implemented on computer software-based and embedded systems, also play an important part in the context of AmI, where they are digital projections of hardware-sensing devices in a virtual space, but can also exist without a physical counterpart; see Jiang et al (2021) for a review. Conjoint examination of radars and other physical and soft sensors is thus recommended in future work.

❻ **Explore new gesture types enabled by radar sensing for interactive computer systems and smart environments.** Gestures sensed by radars can, in principle, capture any type of human movement, including whole-body, head, hand, and arm gestures, and breathing. The underlying movement can be performed either in isolation, e.g., hand gestures, or in combination, e.g., hand and foot gestures.

❼ **Design gesture types specific to radar sensing.** By combining implications ❹ and ❺, radar-based gestures could prove beneficial in contexts of use not covered or supported by other gesture sensing technology. To this end, we propose the following opportunities specific to radar sensing: (7.1) use radars to expand the sensing range of other gesture sensors, e.g., beyond the 70 cm distance from the Leap Motion controller or beyond on-surface gestures for touchscreen input; (7.2) gestures performed in the dark produced in environmental conditions where other sensing technology would fail, e.g., firefighters employ gestures to communicate under extreme conditions, but such communications only work when lighting conditions permit them; when the lighting is insufficient, a distinct set of gestures performed on the body may be used, e.g., on the scapula because it is the largest and flattest bone of the human body. Also, gestures used in aviation, e.g., for landing or refueling, could be considered under foggy weather conditions; (7.3) hidden gestures, represented by gestures produced behind a surface, either translucent, e.g., in front of a store window, or opaque, e.g., behind a door or under the table; (7.4) reflected gestures, represented by gestures produced in other directions than directly facing the sensor or the interactive system by redirecting the radar signal via a reflective surface, e.g., gestures could be picked up by a radar placed in a hallway with the user located in a lateral room with the door open. An example is Solids on Soli (Čopič Pucihar et al 2022), reporting the effect of 81 material types on radar-based gesture recognition accuracy.

❽ **Compare off-the-shelf *vs.* custom-made radars for gesture recognition.** Most of the papers analyzed in our SLR employed custom-made radars using technologies that are challenging to reproduce, which hinders further scientific investigation and exploration of practical application opportunities of radar gestures. In contrast, off-the-shelf radars, such as Walabot (Fig. 1), allow flexible configuration of the integrated emitters and receivers with implications for reproducibility (Villarreal-Narvaez et al 2022) and reusability in the context of open-source practices for scientific research; see also implication ❸. We expect that some of the newest radar technologies will become increasingly available and affordable in the foreseeable future, e.g., the custom-made radar used in (Berenguer et al 2019) has already become available.

❾ **Publicly available radar gesture datasets.** Because of the large size of radar gesture representations and requirements of deep learning techniques, training datasets are frequently very large. For instance, Hayashi et al (2021) used up to 3.68×10^5 positive samples to train a CNN (p. 5:12). Unfortunately, gesture datasets are rarely released. Making data available is crucial for replicability purposes (Villarreal-Narvaez et al 2022; Gheran et al 2022), but also for evaluating the performance of new radar gesture recognizers.

❿ **Identify new locations for radar sensor placement and installation in the environment to enable a variety of gesture types for interactive systems.** Most of the papers analyzed in our SLR did not provide sufficient details about the locations where the radars were positioned to capture users' gestures. When details were provided, typical locations included in-lab settings, an anechoic chamber (Sakamoto et al 2018), or controlled environments with radars carefully positioned. An exception is Pantomime (Palipana et al 2021), which compared several realistic physical environments, e.g., restaurant, office, etc. In the next section, we expand this implication for AmI environments, where interactions are intended to be transparent, intuitive, familiar, and natural to users, but also adaptive and context-sensitive (Cook et al 2009).

6 A taxonomy of radar gesture sensing integration in AmI environments

Our set of implications following the SLR meta-analysis has focused on the need for diversifying application gesture sets to take advantage of the versatility and flexibility of radar sensors for detecting body poses and movements. One particular implication regards the installation of radars in various locations from the environment, from where to sense a diversity of gesture types. In the following, we elaborate on this implication by proposing a taxonomy of possible locations for integrating radar-based gesture sensing for AmI. In particular, we focus on the living room due to the diversity of activities that this space fosters, including conversation, socialization, leisure, play, home entertainment, etc. Our taxonomy extends a preliminary attempt by Siean et al (2022), who focused on gesture-based interactions for smart TVs.

Integrating radars into various objects and digital devices from the living room can provide a uniform way to interact within the AmI environment of that room consisting of an ecology of users, devices, and objects (Marquardt and Greenberg 2015; Greenberg et al 2011) and spanning a wide range of digital content types Vatavu (2022); Schipor and

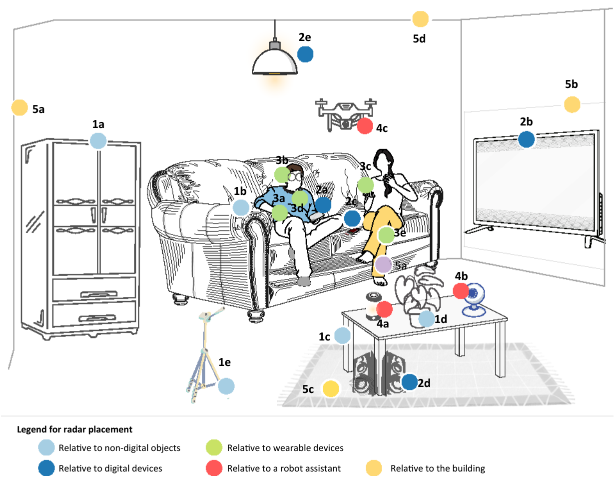

Fig. 7 Various locations where radars sensors can be placed, installed, attached, or integrated. Five distinct categories of the taxonomy are highlighted using colors, e.g., location 4c specifies integration of the radar into a flying robot and location 3a depicts integration into the user's smartwatch

Vatavu (2018). We argue that radars are suitable for such an integration since AmI systems and services are unobtrusive, embedded, adaptive, and transparent (Cook et al 2009). Therefore, we introduce a five-category taxonomy of possible locations where radar sensors can be placed, installed, attached, or integrated in the physical environment, which we describe in terms of use case scenarios involving diverse gesture types and potential applications, e.g., radar sensors integrated in the smart TV, robot assistants, or a smart lamp from the living room. Figure 7 illustrates the categories of our taxonomy and examples of locations within each category.

6.1 Radar sensors integrated into non-digital objects

In this category, radar sensors are integrated into non-digital objects from the living room. We identify the following non-exhaustive possibilities to retrofit physical objects with radar-based gesture sensing and recognition:

(1a) *Furniture.* The radar is integrated into living room furniture, such as a cabinet, which enables sensing of gestures performed with the hands, arms, and the whole body. Two pieces of furniture, the couch and the coffee table, respectively, are considered distinctly in our taxonomy (scenarios 1b and 1c) due to the specific gesture types they enable (Vatavu and Pentiuc 2008; Vanattenhoven et al 2019). Also, radars integrated into furniture near the couch could be used to detect various gesture types from a distinct perspective. For example, a radar integrated into a lamp or a cabinet can pick up the user's gestures while the user is sitting on the couch. Another example is ambient devices, such as the Ambient Monitor,[4] a cylinder-shaped device that allows users to perform gesture input directed at IoT devices from the smart environment. Depending on the position of the user relative to the radar, gestures of the hands and arms, such as "palm tilt" (Altmann et al 2021) and "stand up" (Sakamoto et al 2017), can be detected in the couch vicinity.

(1b) *Couch and couch armrest.* In this scenario, users interact with applications and services from the AmI environment via gestures of the hands and fingers performed on or above the couch armrest. Information about the user's location and body pose could be further exploited for adaptive and context-sensitive AmI services, e.g., volume, stereo balance, and panning of the sound (Lee and Lee 2010), or adaptive systems that integrate end users' preferences for comfortable gestures (Vanattenhoven et al 2019). Examples of radar-based gestures from the scientific literature that can be implemented for this scenario include "push," "pull," and "swipe"; see Fig. 5 for corresponding illustrations.

(1c) *Coffee table.* This scenario enables gestures of the hands, arms, and legs performed with larger amplitude of the underlying movement than the gestures from scenario 1b. Gesture interactions around or below the surface of the table (Avrahami et al 2018) or above and on the table (Vatavu and Pentiuc 2008) are representative for this scenario, during which users transition between "lean back" and "lean forward" interaction. Moreover, the coffee table can provide output, e.g., via an integrated display, speakers, or video projections.

(1d) *Decorative objects.* The same types of gestures as in scenario 1c could be detected by integrating radar sensing into a decorative, non-digital object from the coffee table. What differentiates this scenario from 1c is that the decorative object is mobile and, thus, enables more flexible placement, orientation, and different use cases compared to the coffee table. This setup was mimicked in Sluÿters et al (2022), where a portable radar was placed inside a mobile box on a coffee table.

(1e) *Dedicated stand for the radar.* In this scenario, the radar sensor is placed on a tripod, a dedicated stand, which we found in 11.11% of the papers from our SLR; see Fig. 4. Interactions are performed via hand and whole-body gestures.

[4] https://www.design-burger.com/media/ambient-interfaces

6.2 Radars integrated into digital devices

Radar sensors can be integrated into electronic and computing devices, either personal, e.g., the smartphone, or from the living room, e.g., the smart TV. We identify the following non-exhaustive possibilities for an AmI environment:

(2a) *Smartphone/tablet.* In this scenario, users can employ both radar gestures and conventional touchscreen input to interact with the device and in the AmI environment. For example, the Soli radar was integrated into a smartphone to enable specific gesture interactions, such as swiping over the smartphone (Lien et al 2016).

(2b) *TV set.* The TV represents the main home entertainment device from the living room and, thus, holds a privileged position in our taxonomy. Possible gestures are represented by hand poses and movements in mid-air as well as whole-body gestures (Vatavu 2012; Freeman and Weissman 1995; Stec and Larsen 2018), e.g., "click" (Wang et al 2020a; Bannon et al 2020) for selecting options shown on the TV screen; see Fig. 5.

(2c) *TV remote control.* A particular case for scenario 2b regards integration of the radar into the TV remote control, which enables combined gestures with the remote control (Bailly et al 2011), above, and around it.

(2d) *Soundbar/speakers.* We equally propose integrating radar sensors into the audio system of an AmI environment. Examples of hand gestures include repeated "push" for decreasing the audio volume or a whole-body gesture, such as "stand up" followed by the user exiting the room, to turn off the music; see Fig. 5.

(2e) *Smart lighting.* Integrating radar sensing with smart lighting systems will foster new interactions with light (Andrei et al 2022; Lucero et al 2016; Offermans et al 2014), but also gesture-based input sensed by ambient devices that provide feedback using light.

6.3 Radar sensors integrated into wearables

In this category, radar sensors are integrated into devices designed to be worn or affixed to the users' body and clothes:

(3a) *Smartwatch/Fitness tracker.* By integrating the radar into a device worn on the wrist, various hand gestures, e.g., above the smartwatch, head gestures, e.g., looking at the device, or breathing could be detected and employed for interactive purposes. Small radar chips, such as Soli (Lien et al 2016), could potentially be used for integration into future smartwatch models.

(3b) *Smart glasses/Head-mounted displays.* Conventional gesture input for smart glasses and head-mounted displays involves touch gestures performed on the glasses temples (Islam et al 2018) and head movements (Yan et al 2018). Integrating radars into devices worn on the head and at eye level would expand their sensing range with mid-air gestures performed with the fingers, hands, arms, and legs. Just like for scenario 3a, the unique vantage point delivered by a wearable enables distinct opportunities for detecting specific gesture types.

(3c) *Smart rings.* Integration with small wearables could enable interactions performed using microgestures of the fingers, gestures of the opposite hand, the arm, and the head, respectively. Such gesture types, sensed from the vantage point of the index finger wearing an electronic ring (Vatavu 2023), would complement gestures sensed with other technology, such as inertial sensors already embedded in electronic rings, towards implementing gesture sets that reflect more closely end users' preferences (Gheran et al 2018).

(3d) *Smart jewelry.* Integrating radar sensing into devices designed for various parts of the body or that can be worn on different locations will further increase the versatility of radar-based gesture interaction; also see 3e.

(3e) *From smart wearables to smart clothes.* We found in our SLR two papers that examined radar sensors attached to the body: Li et al (2015) placed a radar sensor on the neck to enable gestures performed with the tongue, and Čopič Pucihar et al (2019) placed the Soli radar on the wrist to sense microgestures on physical objects. These use case scenarios can be implemented either in the form of wearables, but also via integration into clothing, following recent technology trends (Poupyrev et al 2016), for deploying invisible ubiquitous interactivity at scale via interactive textile materials.

6.4 Radars integrated into robot assistants

In this category, radars are integrated into digital devices that take the form factor and function of robot assistants. We identify the following non-exhaustive possibilities:

(4a) *Voice assistants.* Personal robot assistants that accept interactions via speech input have increased in popularity. By integrating radar sensors, a dual goal could be achieved: (i) enrich the interaction modalities for personal assistants and (ii) use personal assistants as sensing devices for gestures directed at other systems from the AmI environment. Examples of gestures from our SLR include "push" and "pull" to increase and decrease the audio volume, respectively; see Fig. 5.

(4b) *Robot assistants.* Unlike personal voice assistants that are still, mobile robots can follow the user, occupy different locations in the room, change location, and perform various services, such is the case of robot vacuums.

(4c) *Drones.* As a special category of robot assistants, drones benefit of higher mobility, and many models implement "follow me" functionality (Abtahi et al 2017).

6.5 Radars integrated into the building

In this category, the radar sensors are integrated into the architectural elements of the room, as follows:

(5a) *Walls.* Walls, as large surfaces, can be leveraged for both input and output in the context of AmI environments, and radars already have applications for sensing through the walls. For example, Walabot[5] is a commercial radar with applications including pipes detection in the wall.

(5b) *The wall behind the TV screen*. Just like the TV was considered distinctly in our taxonomy (scenarios 2b and 2c), the wall behind the TV screen presents unique interaction opportunities. For example, a video projection on the wall behind the TV can enrich the content rendered on the TV screen (Jones et al 2013). Thus, radar sensing could be integrated in the wall behind the TV screen to enable scenario 2b, but also gesture input addressing other interactive systems from the AmI environment.

(5c) *Floor.* When the sensor is positioned on or near the floor, it offers a distinct vantage point to capture various gesture types (Bailly et al 2012).

(5d) *Ceiling.* Complementary to scenario 5c, a radar sensor placed on or near the ceiling also offers distinct possibilities to detect specific gesture types. The radar could be integrated into decorative elements from the ceiling, which would privilege the detection of arm and head gestures performed at the zenith of the user's body.

7 Conclusion

We conducted a systematic literature review to analyze recent developments in radar-based gesture recognition through the prism of application types and corresponding gesture sets for interactive computer systems and smart environments. Our results revealed gesture sets composed of few and simple gestures, a bias towards technical performance evaluation centered on the system, while mostly neglecting the user experience with radar gestures, and an inconclusive trend for applications that implement radar-based gesture interactions. By capitalizing on these findings, we proposed ten practical implications for future work towards making radar-based gesture interaction more expressive. As radars become increasingly accessible and affordable, we expect to see more applications of radar-based sensing, enabling new interactions with computer systems and smart environments (Yeo and Quigley 2017). Also, given the increasing adoption of smart home technology, including smart lighting, smart assistants, online digital services, IoT products, etc., we expect further integration of new user input sensing technology, such as enabled by radars, in the physical environment towards implementing the vision of AmI (Cook et al 2009; Epstein 1998; Aarts and Encarnação 2006). To foster such integration, we explored in detail one of our implications, for which we proposed integration of radar sensors into diverse physical locations from an AmI environment with a corresponding taxonomy of digital devices, non-digital physical objects, robot assistants, and architectural elements, respectively. Finally, the increasing availability of virtual and augmented reality technology will likely foster new advances in terms of interactions that span across smart environments and virtual worlds, enabled by the shared philosophical overlap between the computing visions of AmI and augmented reality (Vatavu 2022). This favorable technological context sets the foundation for further innovations in designing interactions, based on natural gesture input, for smart environments of many kinds.

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Declarations

Conflict of interest The authors declare no conflict of interest.

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[5] https://walabot.com

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