The Internet of Social Robots with Things (IoSRT)

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This literature review explored how ultra-wideband technologies may advance social robotics in the commercial domain, considering robot-human recognition and user modelling. Three existing articles entered the review, two were enriched using the systematic mapping study approach, following exclusions 123 papers entered into the inquiry. Focus areas included understanding how diminished user exposure affects adaptivity in social robots, their recognition modalities, impact of face masks, user modelling architectures and existing ultra-wideband implementations within the wider robotics realm. Results demonstrated the multi-faceted dependencies social robots have with faces, limited user exposure led to loss of key features, ultra-wideband had not been applied with social robots. Exploration of user modelling techniques points to Bayesian inference as a way to inform dialogue strategy. The next generation of social robot in the commercial space may be defined as an instrument within the wider cyber-physical system where it becomes a socially intelligent, knowledgeable agent. Ultra-wideband combined with systems from Industry 4.0 appear to not only hold the key to identifying humans accurately but could also add pseudo-autobiographical memory that does not require prior user exposure.

Introduction

A marketing personalisation cobot was prototyped in conjunction with Porsche. Their interest in Social Robots (SR) demonstrates that significant opportunities exist in the commercial retail domain, but the project highlighted several problems. User Modelling (UM) presents a challenge as robots may not have prior contact, and user recognition can involve inhibitive levels of administration. Ultra-WideBand (UWB) technology may introduce solutions to those issues, and learning is available from industrial systems architectures. This paper introduces the key areas before reviewing the State-of-the Art (SOTA) covering questions aimed at advancing to Proof of Concept (POC).

Robot Human Recognition (RHR)

RHR in a commercial or retail environment can be challenging to implement. Customers may feel uncomfortable providing facial data. [1] researched attitudes toward facial recognition (FR) systems and found the public did not trust the private sector, finding only 7% supported covert use in supermarkets. Covid-19 face masks have also become a problem for FR [2]. Improvements have been demonstrated by researchers, but despite their efforts, systems do not perform reliably [3]. General Data Protection Regulations (GDPR) control profiling and algorithmic decision-making systems [4], this introduces a risk where misidentification could lead to a data breach, loss of trust, reputational damage and financial penalties for companies involved [5].

Robot Social Intelligence (RSI)

Ensuring smooth RHR is central to delivering automated between-user SR personalisation, but the robot must also be socially intelligent, within-subject adaptive, and contextually aware. Social intelligence (SI) in humans is complex and multi-dimensional. Human cognition is developed gradually [6] and has evolved from monkeys [7]. Shared exposure to contextual factors increases cooperation [8] and paying attention to the interests of the other increases SI [9]. Human social bonding experiences are autobiographical, memories fuel reminiscence and lead to motivation to repeat experience with the other [10]. Mimicry of these human SI traits is key to SR success.

Extant literature on SR explains how solutions have evolved from early attempts to embed artificial social intelligence [11; 12; 13; 14; 15]. Early work was based on philosophical and social psychological theories. Later studies evolved taxonomies [16; 17; 18]. Early literature reviews (LR) found robot SI had advanced in areas including emotional recognition, vocal dialogue skills and dynamic reciprocal embodied expression. Deep learning and Artificial Intelligence (AI) have more recently enhanced SR adaptivity, rapport building, empathy reciprocation, and contextual awareness skills [19]. The latest features may require full face visibility and be heavily dependent on time spent UM. It is therefore important to consider how transferable robot social skills are between domains. Transferring SR into the commercial environment may limit functionality, adaptiveness and reduce social knowledge.

Internet of Robots with Things (IoRT)

The Internet of Things (IoT) is a collective term for intelligent devices (*things*) that sense and communicate data via the internet [20]. The Internet of Robots with Things (IoRT) incorporates IoT data in ways that support robots in achieving their purpose [21]. The IoT has been central to advancement of Industry 4.0, the fourth industrial revolution [22] where devices are collectively referred to as the Industrial Internet of Things (IIoT). As with military and space exploration technologies, industrial innovation trickles down and is often adopted by other domains. Smart factory mobile autonomous robots rely on IIoT devices to identify materials [23], automate task scheduling [24], and work together efficiently [25]. Digital Product Memory (DPM) combines information from the IIoT, including positioning and environmental data throughout production, storage, and shipping [26].

Collectively some of these systems and their associated architectural models may be useful for SR, not only to resolve RHR problems but also to advance their social knowledge within circumstances where they have little or no exposure to users in the same way as IIoT gathers data on products.

Indoor radio wave technologies allow industrial robots to trilaterate tags wherever they are in space at any given time, fixed or mobile. Historically, methods have included Wireless Fidelity [(Wi-Fi); 27], Wireless Local Area Network [(WLAN); 28], Bluetooth Low Energy [(BTLE); 29], and Infrared [(IR); 30] but their accuracy is <0.7m and would not overcome misidentification risks associated with RHR. However, UWB may be suitable, as its positioning error is <10cm [31]. UWB used to be restricted to military use [32] but has become commercially available and applied within smart factories over the last decade [33]. Initially, it was expensive until recent low-cost modules were introduced [34]. Trilateration data can be stored over time to explain tracking behaviour within a space when presented as a choropleth map [35]. The same data may be useful when fused into UM to inform SR acting as a form of autobiographical social knowledge. The UWB tag therefore transforms industrial Digital Product Memory (DPM) into useful information about user location over time that can inform dialogue.

Research Questions (RQ)

RQ1: What options, other than FR, do robots have to identify the user?
RQ2: Where faces are obscured by masks, what implications does this have for the SR?
RQ3: How does having no prior user exposure limit SI features of the SR?
RQ4: How is UWB applied with robots to date? What can be learned from examples of methods of implementation?
RQ5: Considering how UWB may combine with any information the commercial organisation has relating to the user, which methods are SOTA that can be used to advance RSI and knowledge?

Method

The traditional LR involves a keyword search approach across journals before filtering by relevant criteria. Due to time constraints, the methodology selected for this article was a hybrid between the LR and the Systematic Mapping Study [36]. This approach takes the most relevant existing paper(s) before content enrichment, in this case using the Connected Papers web service [37] to ensure inclusion of the most up-to-date SOTA articles.

Search process and enrichment

Initial search employed Google Scholar [38] to find the three most up to date surveys covering SR [39], UWB applied within the robotics realm [40] and SR UM [41]. Enrichment was only applied where the article(s) were not entirely up-to-date [39, 41]. Papers listed within articles were enriched. Results producing more recent material fitting the original criteria were added.

Filtering criteria

A) RQs 1-3 were based on an enriched SR paper by [39]. 56 articles were run through connected papers, adding 23. 89 papers were reduced to 69, filtered to research including areas covering RHR and UM techniques.
B) RQ4 was based on papers identified in an UWB robotics article by [40]. 106 papers were reduced to 40, filtered to research including solely robots and / or UWB implementation.
C) RQ5 was based on an enriched SR UM paper by [41]. 18 papers were run through connected papers adding 6. 24 papers were reduced to 14, filtered to research including solely UM techniques. Papers from (A) were combined, leading to 83.

Data collection

Following exclusions, all papers were coded according to research question requirements. Results chart labels indicate taxonomical categorisations.

Results

RQ1:
What options, other than FR, do robots have to identify the user?

69 papers were categorised into 30 theoretical and 39 directly implicating robots. Figure 1 shows 3 were Wizard of Oz (WoO), 24 Assumed User Constancy (AUC), and 12 were Between-User Adaptive (BUA).

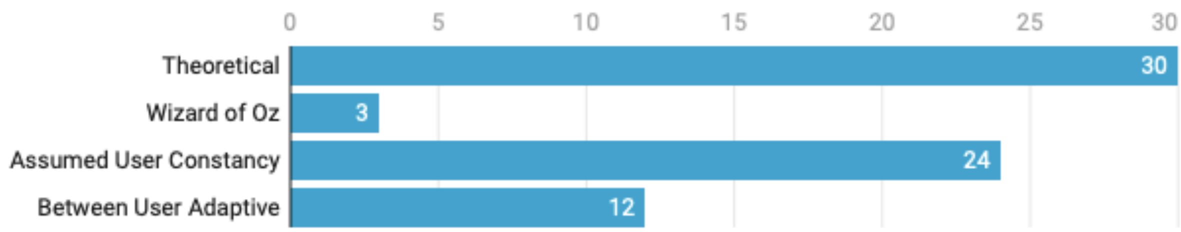

Figure 1. High level robot RHR categories.

Within BUA, all 12 primarily employ FR. Figure 2 highlights how 8 had a secondary means available. Seven entered into dialogue. One used a wearable device.

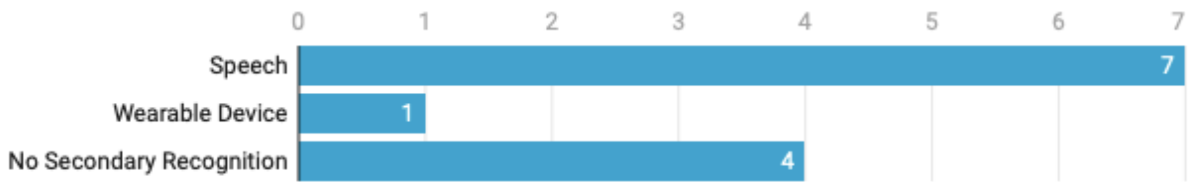

Figure 2. Secondary means of recognition.

Figure 3 breaks down the 7 robot platforms that employed conversational backup. They were mainly based on Nao [42; 43; 44], but others included iSanbot [41], Brian [45], i-Cub [46] and an unnamed advanced care robot [47]. One Nao robot could identify users with a wearable [48].

Figure 3. Robots with secondary adaptation means.

The 4 with no secondary mechanism either moved to AUC [49; 50; 51] or failed entirely [52].

RQ2:
Where faces are obscured by masks, what implications does this have for the SR?

Of 39 robots, 24 recognised emotion using FR. Figure 4 shows how of 12 BUA robots all lost emotional recognition functionality where masks were worn. Five specialised in emotional reciprocity [49; 45; 41; 53; 51], an important feature central to their purpose.

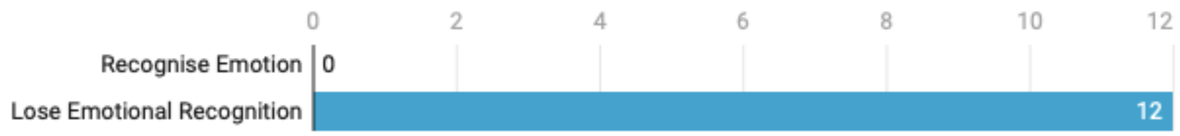

Figure 4. Face mask impact on BUA robots.

Of 24 AUC robots, Figure 5 demonstrates that 11 used facial emotion as part of their primary function, 6 fail entirely [54; 55; 56; 57; 58; 59] and became unfit for purpose. Five largely failed and lost most functionality [60; 61; 62; 63; 64].

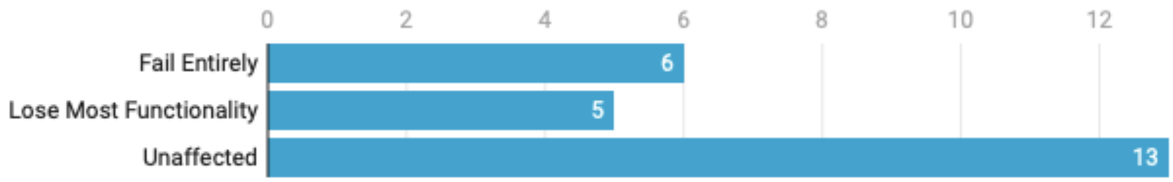

Figure 5. Face mask impact on AUC robots.

Of 3 WoO robots, Figure 6 shows how only one was negatively affected as it automatically reciprocated facial emotion [65; 66; 67].

Figure 6. Face mask impact on WoO robots.

15 robots that did not fail were all from AUC and WoO categories. Figure 7 shows how they specialised in other areas, including gaze [68; 69; 65; 70; 71; 72; 46; 73], gestures [68; 74; 75; 73; 76], proxemics [68], verbal [77; 78; 79; 74], tactile [65], object affordance [80; 75] and heart rate [81].

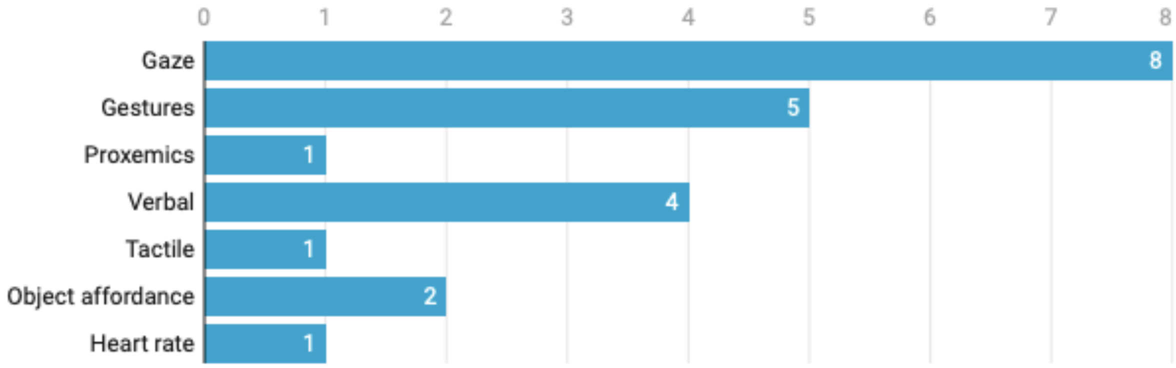

Figure 7. AUC and WoO specialisms not affected by masks.

RQ3:
How does having no prior user exposure limit SI features of the SR?

Figure 8 shows UM types defined to consider the impact of limited user exposure. When including WoO systems, 7 AUC category robots had static user models with pre-trained features applied indiscriminately. 17 remaining were used to develop modular functionality. WoO systems included 2 designed for children with Autism Spectrum Disorder (ASD) [65; 66] and one Defense Advanced Research Projects Agency (DARPA) project. Those systems were teleoperated and unaffected by lack of contact. Dynamic and BUA are further detailed below.

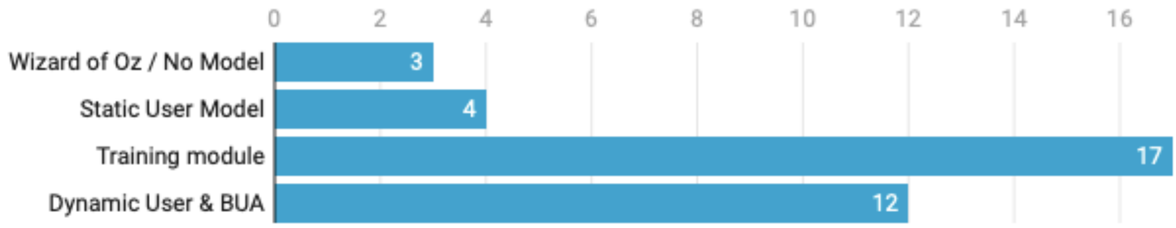

Figure 8. UM types defined to consider limited user exposure.

The 12 BUA robots had more advanced UM. User exposure over time affected BUA robots in different ways. Figure 9 breaks this down into 5 main categories, including 3 Personalised Expression Self Other (PESO), 3 PESO incl. environmental context, 1 user specific assistive, 1 positive reinforcement, and 4 multi-user Short-Term Memory (STM) robots.

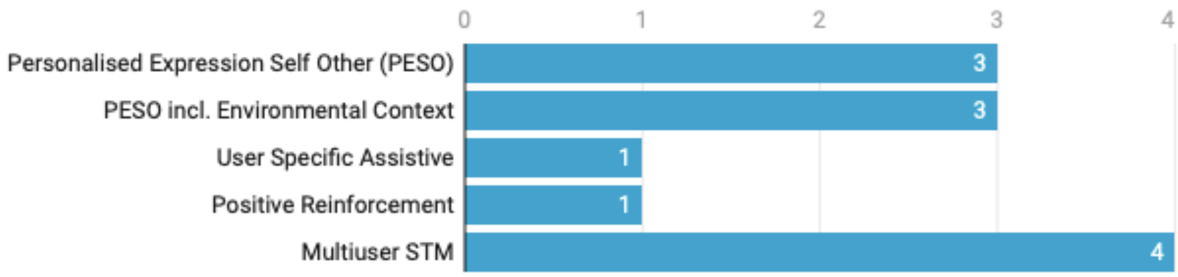

Figure 9. UM categories found within BUA robots.

PESO robots adjusted output over time following user learning. iSanbot [41] asked users questions and studied user emotional response over time, leading to personalised questions such as “are you feeling better today.” User goals were also built into some robots within-category [61; 59]. PESO including environmental context, went further to associate categorised object proximity with usage [46], others incorporated combinations of situational and environmental cue learning [43; 73]. [52] implemented an assistive robot that identified elderly users individually to tailor its functionality to their needs. [48] found positive reinforcement could be applied in the home by incorporating UM data from wearables and connected home devices to encourage positive habit formation. Multi-user STM robots are BUA but can be introduced in within-session. They learn about the user, apply knowledge between users, but then reset [42; 81; 62; 50].

RQ4:
How is UWB applied with robots to date? What can be learned from examples of methods of implementation?

40 papers were included in the review by [40], 23 involved robots. Figure 10 shows how they broke down into categories, including 12 Unmanned Arial Vehicles (UAV), 6 Unmanned Ground Vehicles (UGV), 2 small lab robots, 2 robotic arms and 1 Coal Mining Robot (CMR).

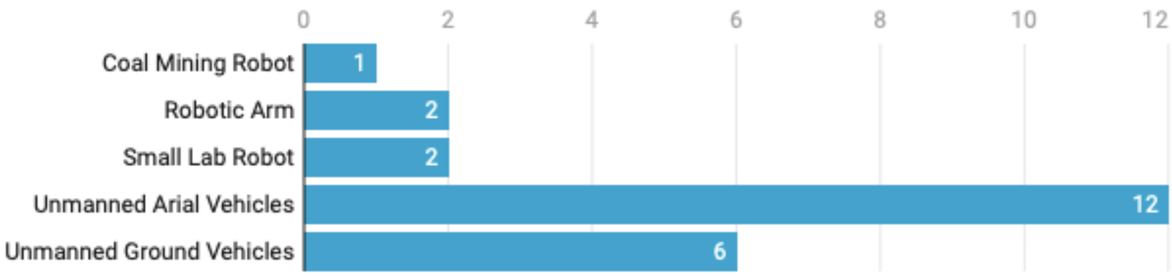

Figure 10. UWB robot implementation types identified by [40].

Two transceiver configurations were identified. The fixed anchor approach [82] where transceivers are placed throughout the area robots are in use. UWB tags transmit signals that are trilaterated between anchors, that positioning data is used to navigate the robot(s). Alternatively, a transceiver is added to the robot, with or without anchors allowing for collaborative localisation [83; 84] where navigation is managed as a swarm. This this configuration can also decentralised [85]. Trilateration accuracy was tested. Positioning error was consistently <75mm where anchors were placed within 20m [82; 86]. Decawave, Ubisense, and Bespoon manufacturers were compared by [87]. Figure 11 highlights how Decawave most accurate relative to other vendors.

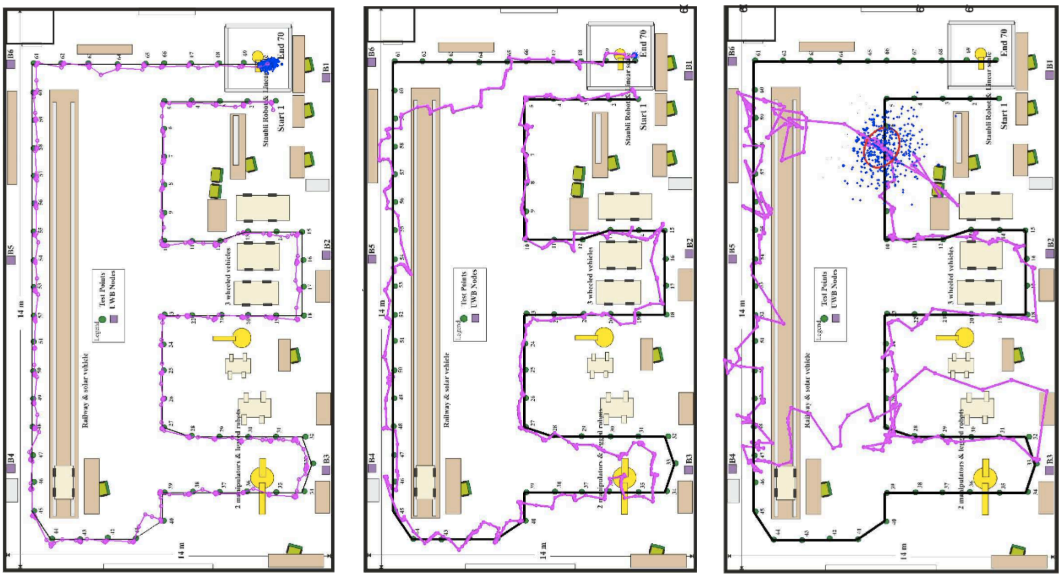

Figure 11. Decawave (left), BeSpoon (centre), Ubisense (right) accuracy comparison.

Resolution refers to time between trilateration measurements. Sampling can be low frequency, such as 10s, through to ~<100ms. [82] implemented an athletics track system recording values at ~100ms but this could be reduced in other applications. Reducing resolution saves data, allows for higher tag densities, and extends battery life [88]. Scalability was considered, calculating the theoretical maximum number of tags usable within one system. Based on bandwidth and calculation of varying resolution payloads, they estimated between 254 and 6171 [88]. [40] also highlighted solutions, including body orientation measurement [89; 90] and human-robot collision avoidance [91].

RQ5:
Considering how UWB may combine with any information the commercial organisation has relating to the user, which methods are SOTA that can be used to advance RSI and knowledge?

The literature included some extant papers that explained how early SR employed teleoperation architectures and simple logic-based systems [92]. Persona models were introduced by [93] based on group characteristics leading to early SR adaptivity. 83 papers highlight SOTA approaches to UM shown in Figure 12, including 3 fuzzy logic based, 5 neural networks, 5 stochastic, 2 probabilistic, and 4 mixed systems.

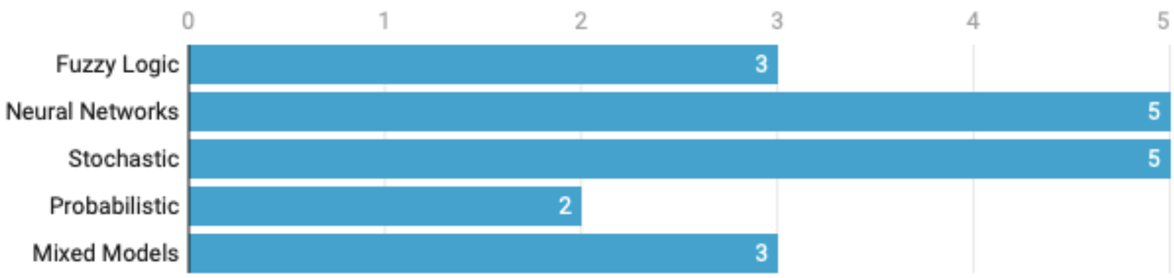

Figure 12. UM statistical approaches.

Fuzzy logic algorithms were used to decide the ideal time to interact with elderly users based on interpretation of body state over time [73], to optimise movement trajectories whilst following users [94] and to allow an expressive robot to reciprocate emotion [44]. Machine

Learning systems included a Random Forest Classifier (RFC) to adapt robot behaviour to individual elderly group members [50]. Support Vector Machines (SVM) trained to allow a service robot to interpret verbal commands [95] and a robot that could interpret whether user behaviour indicated desire it to interact [96]. Neural networks were applied to two robots in ways that allowed them to classify user video imagery. A Supervised Multiple Timescale Recurrent Neural Network (SMTRNN) was used to forecast user intent based on how they approached objects [75]. A convolutional neural network trained a robot to mimic facial expression [56]. Stochastic models were all Markov. Four systems used the Markov Decision Process (MDP) to empathise and reciprocate emotion [45; 97; 53; 98]. One Partially Observable Markov Decision Process (POMDP) model was used with a robot arm to demonstrate robot-human adaptation during collaborative problem-solving tasks [99]. Probabilistic models applied were Bayesian inference and based on iterations of the same design; the Bayesian User Model (BUM). Simulations of user information were informed by wearables, connected home devices and robot modalities. Cloud data fusion preceded UM updates being sent to the robot to refine adaptivity [100]. BUM later incorporated cultural awareness, it was partly successful but concluded future work should explore POMDP models [101]. Mixed models included two combined Bayesian and Markov systems, one predicted user choices in elderly care service robots [102], another a novel cognitive architecture for SR based on NAO that could dance creatively alongside humans [43]. A MAXQ reinforcement learning system was applied to a socially assistive game playing SR for users with cognitive impairments. It could adapt between opponents [81].

Discussion

RQ1:
What options, other than FR, do robots have to identify the user?

Many SR assume that all humans are the same user, other BUA robots are adaptive, most of which possess backup recognition systems. Voice recognition was the most common standby modality. This may be ideal for home and laboratory use but could be problematic elsewhere in busier, noisy environments. One robot used a personal wearable device which is similar to the UWB tag concept. This may in itself be considered as an alternative solution to RHR, but it would introduce greater privacy issues, and have accuracy problems as highlighted in the introduction. The SR surveyed were generally designed for use outside the commercial domain, where facial recognition may not be a problem.

RQ2:
Where faces are obscured by masks, what implications does this have for the SR?

Robots across all categories fail to recognise facial emotion when masks are worn. Many are sold on their ability to reciprocate user facial expression and become unfit for purpose. Whilst many of the SR within the literature reviewed may operate in domains where masks are not always required, they certainly present a major problem for commercial retail application. AUC robots were mainly unaffected by masks and specialised in other areas, this made up around one third of all robots surveyed. The majority were experimental systems focused on gaze, gesture, or verbal cues. WoO systems could continue to be teleoperated. Future work should search for SOTA museum robots, they have a history of success [104] and could identify further learning for the wider investigation.

RQ3:
How does having no prior user exposure limit SI features of the SR?

Most SR have built in transferable non-user dependent generic functions, but BUA robots rely on UM over time and require prior exposure to build social knowledge that, in turn, allows them to react differently between individuals. Without it, they cannot succeed in their goal. BUA robot sub-categorisation highlighted how UM specifically explained functional adaptation. Half enhanced expression by UM empathy combined with situational context. One fused wearable and connected home data to initiate dialogue that promoted healthy habit formation. Socially assistive robots customised their functionality based on intra-individual task-type request frequency over time. Multi-user STM robots applied UM that enhanced between-user adaptation then reset after fulfilling their short-term goal. Future work should expand research to consider cognitive architectural features applied by [48] as their work also employed IoT technology. Reflecting on privacy and regulatory considerations, multi-user STM systems should be investigated further as this model could potentially mediate user attitude toward risk against reward.

RQ4:
How is UWB applied with robots to date? What can be learned from examples of methods of implementation?

UWB had not been applied within the SR domain. Trilateration performance was reported as accurate enough to overcome RHR issues and can be confirmed as the only indoor positioning technology currently on the market that could achieve this. The fixed anchor approach to locating transceivers is the most suitable for SR applied in the commercial retail environment. It allows for remote processing, reduces cost, and does not require robot hardware modification [40]. Positioning sample rates can be varied between 10s and 100ms, the setting of which is dependent upon expected tag movement velocity. Future work in this area is needed to validate assumptions about efficacy of UWB as adequate for overcoming RHR problems.

RQ5:
Considering how UWB may combine with any information the commercial organisation has relating to the user, which methods are SOTA that can be used to advance RSI and knowledge?

Models identified across the literature when analysed together demonstrate the specialisms of UM statistical approaches employed by SR. Results clarified direction for future work. Markov models work well for UM emotion and in areas affording long-term exposure, but supervised Bayesian structural time series analysis provides the ideal probabilistic means to enable RSI in conjunction with UWB. The SR can be empowered to not only accurately recognise users, it can gain social knowledge as part of a cyber-physical system even without direct prior exposure in person by analysing UWB tag positioning data combined with referential locus information over time. Future work in this area needs to simulate an example application, such as a trade exhibition. UWB positioning time within-locus-against-loci can be translated by the SR into intelligent dialogue in the same way as humans:

“I saw you spent time at the Siemens exhibit. Would you like to connect on LinkedIn to Simon, the expert you spoke to?” or, ”You spent 10 minutes talking to the ABB representative, would you like his details?”

Conclusion

For social robots, as with humans, a clear dichotomy exists between social intelligence and social knowledge. One is about ability; the other is about exposure and access to learning. Issues with robot-human recognition introduced because of facial data or mask use and user modelling problems related to exposure time are largely domain specific. Experimental robots, or those used in the home, can overcome these barriers, but currently they would fail a commercial retail project. The social robot is limited in terms of its cross-domain transferability, but UWB appears to provide a solution to many of the problems presented. The technology, if combined with the correct approach to user modelling, may supply social knowledge to a robot that would enhance its ability beyond that presented in the current literature. Models that provide a system with a limited memory span may be the answer to building user trust. UWB is a versatile, useful way to solve robot recognition and user modelling problems. IoT enabled Industry 4.0 technologies have inspired this paper and could also hold the key to further progressing the field.

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