2 Human-Robot Interaction

Robotic systems generally entail six categories of human interactions [6] applicable to retail settings: proximity, autonomy, human-to-robot signaling, sensors, robotic platforms, and HRI systems [1, 4, 5].

2.1 Types of Proximities

Human–robot interactions are proximate or remote in the sense of physical distance [12, 13]. Proximate interactions occur between operators and robots who communicate directly or indirectly at the same place and time [9]. Examples of proximate interaction are robotic toys and mechanisms operating autonomously or guided by nearby humans [11, 14]. Remote interactions are spatially or temporally separated (Figure 1). Teleoperation is an example, although interactions in extreme conditions—e.g., disaster relief, deep sea operations, or high-altitude and long-range unmanned aerial vehicles—are best known for their applications [12]. Robots in retail businesses are generally expected to interact proximately with customers, but they could be managed remotely by distant operators and fully autonomous operation is possible [15].

Fig. 1 Proximate interaction: the mobile manipulator Loki (top). Remote interaction: a human-operated multi-copter (bottom).

2.2 Levels of Autonomy

Autonomy is the extent to which robots perform tasks independently [13, 16]. Limited autonomy could be arguably best in retail contexts, as it allows firms to maintain manageable workloads and control their robots [17]. Sheridan and Verplank [18] describe ten levels of autonomy ranging from completely human-controlled to fully autonomous (Table 1) which suggest that robot users or operators are recommended to choose most appropriate ones for their applications.

2.3 Human Signals

Current robotic technology employs various types of human-to-robot biological signals such as electromyography (EMG), face, figure and hand, speech and voice, or combination of them. Besides reducing failure rates and computational time [14], bio-signals maximize interactive efficiency using humanlike recognition, perception, engagement, determination, and decision-making [17, 19].

2.3.1 Electromyography

Electromyographs (EMGs) detect electricity generated by muscle contractions or brain activity. EMGs require direct physical interface—remote or tethered—between robots and operators, who wear an apparatus that transmits their body's electrical signals [20]. Their many applications to HRI include teleoperation in harsh and remote environments [21] and advanced medical prostheses [22], exoskeletons [23], and muscle-computer interfaces [24]. Their retail uses include interactions with children [25], in robots that cooperate with employees [26]; [27], in teleoperation of redundant robots [28], and household service [29]. Their disadvantages include the dimensionality and complexity of human musculature, the non-linear relation between human myoelectric activity and motion or force, muscle fatigue, signal noise, and exogenous factors such as sweat and weather [30, 31] which often requires extesive data and machine learning process (Figure 2 and 3).

Fig. 2 Cyberglove II flex sensors based MCS (Cyberglove Systems image)

Fig. 3 Robot torso controlled by EMG signals (DLR photo)

2.3.2 Face

Intelligent robots often use vision systems to avoid obstacles, detect objects, navigate, and execute tasks, but facial recognition technology is necessary for proximate human–robot interactions. Besides mechanical vision hardware, facial recognition requires mathematical models and sophisticated algorithms to perceive, recognize, and react to facial characteristics collected by a camera [32] (Figure 4). Once the face is detected, it normally must be tracked if programmed tasks are to be performed correctly [32-39]. Faces present greater pattern-recognition problems (colors, shapes, influence of external conditions) than numbers and letters in static and dynamic contexts [36]. Impediments to retail application include systems' mechanical and mathematical sophistication, dependence on image quality, need for learning algorithms, and environmental limitations.

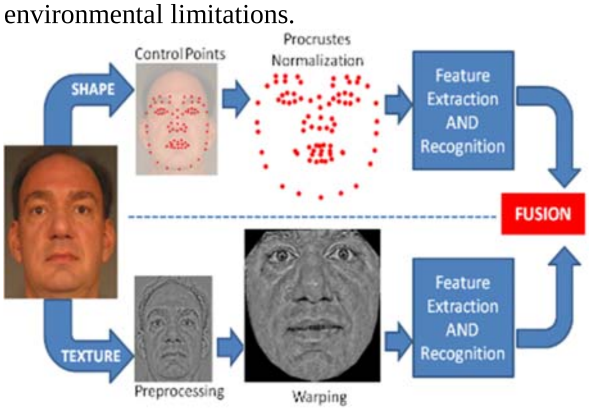

Fig. 4 Face recognition process diagram (CMU photo) and a captured image [40]

2.3.3 Finger and hand

Manual gestures are distinctive signals comprehensible to robots [5]. Characteristics of palms, fists, and finger gestures are more regularized than facial data, but difficulties afflicting this technology include complex and changing backgrounds, variable light conditions, deformities of the human hand, and real-time execution dependent on users and devices (Figure 5). Also, the technology is limited by the number patterns and its applicability to the elderly, young, and disabled. M.W. Krueger first proposed gesture-based interaction as a form of human-computer interaction in the mid-1970s [41], and numerous studies followed [3, 5, 7, 14, 42-45].

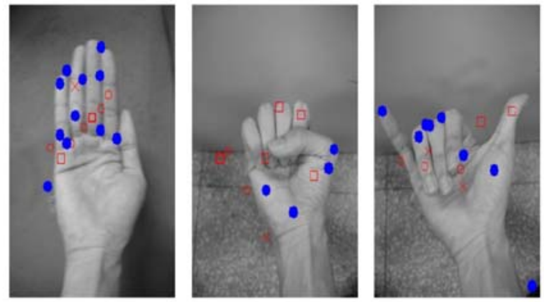

Fig. 5 Images of hand gestures and feature extraction [43]; [46]

2.3.4 Speech and voice

Initiated in the 1950s, speech recognition has been adapted to HRI since 1970 [47] (Figure 6). If systems are adapted to specific users or operate under low-noise conditions, current technology attains acceptable recognition of words and sentences spoken in varying tones [47]. In HRI, the need for robust and automatic speech recognition is still imminent [9, 48, 49].

Fig. 6 Depiction of speech recognition [48]

Speech recognition hardware has expanded enormously, but many problems remain. Noise-cluttered environments impede performance [49]. Systems must be adapted to environments and users both, which customarily involves data learning, sound localization, and multi-pass decoders [50-56].

2.4 Sensors

Robots need sensors to receive data from human operators or their operating environment. There are many sensors already implemented on robots but ones that are most commonly used in HRI are introduced here. One of the most widely used for HRI [33] is vision systems that integrate and process captured images to generate decisions dependent on extant or created databases. Another is the usage of microphones which receive voice commands and enable robots to recognize operators' characteristics [53]. Tactile sensors facilitate physical interactions such as shaking hands and avoiding obstacles [57]. Haptic sensors often incorporate tactile *sensors* that measure forces exerted by the operator.

2.5 Robot Platform

The term "platform" refers to how robots move. Wheeled, mobile, and legged robots are common platforms [2]. Wheeled robots are categorized by the number, driving mechanism, and type of wheel. For instance, a wheelchair is a two-wheeled platform with a differential drive wheel. One advantage of wheeled robots is that their kinematics and dynamics are amply analyzed and modeled [44]. The most common robotic platforms have applications for navigation, path planning, surveillance, reconnaissance, and search and rescue. The Mars Rover [58], unmanned aerial vehicles, drones, and unmanned cars [59] have been tested for military and commercial applications (Figure 7 and 8). Bipedal robots resemble humans and employ assorted modes of mobility. Drones or aerial vehicles have shown for delivery, rescue, and surveillance.

2.6 Human-Robot Interaction Systems

Several HRI systems are commercially available. SoftBank's Pepper mimics human emotion by analyzing expressions and voice tones Fig. 9 Its open-development platform allows users to personalize contents and modify functions.

Fig. 9 Pepper service robot from Softbank

3 Conclusion

This study extends the literature of business technology by demonstrating the potential of human–robotic interaction for retail settings. It is intended to inform retailers about the status and evolution of interactive technologies applicable to their businesses. It has shown how robots can improve customers' retail experience and retailers' efficiency. Future studies need to expand upon our presentation by examining more specific aspects of robotics applicable to retail settings, such as social signals, cultivation of trust, and addition or modification of features that improve human–robot interaction.

Table 1 Sheridan and Verplank's Levels of Autonomy (LOA) [18]

Scale	Autonomy level description
Level 1	No computer assistance; human does everything.
Level 2	Computer offers users a full selection of actionable alternatives.
Level 3	Computer narrows users' selection of choices.
Level 4	Computer suggests an action.
Level 5	Computer executes actions after operator approval.
Level 6	Computer allows operators a limited veto before executing tasks automatically.
Level 7	Computer executes automatically then informs the operator.
Level 8	Computer executes automatically and informs the operator only if requested.
Level 9	Computer executes automatically and informs the operator at its discretion.
Level 10	Computer acts autonomously without informing the operator.

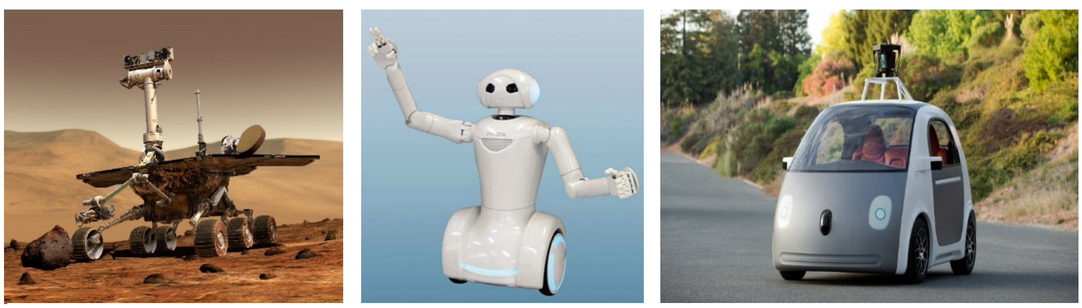

Fig. 7 (a) Mars Rover, (b) Toyota DJ robot, (c) Google's unmanned car.

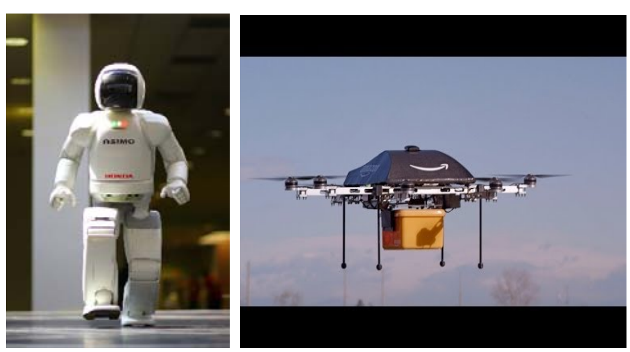

Figure 8 (a) Honda Asimo Humanoid robot [60] (b) Amazon delivery drone

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