Applying Human-Robot Interaction Technology in Retail Industries

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***Abstract*—This review of human–robot interaction technology (HRI) suggests how retailers can enhance customer service and improve their operations through the use of service robots. We have reviewed earlier studies and have identified current and emerging robotic technologies as potential retail game changers in business. The review of HRI technologies presents actionable information that can help retailers stay relevant with consumers during their technological development of the service system. Although extensive research has investigated the psychological, neurological, and engineering issues of HRI, few studies have established how robot technology can elevate customer service and transform the retail industry. This study explains the technological innovations that enable autonomous robots to offer unique consumer experiences that have noteworthy potential for assisting elderly and physically challenged consumers. This study covers primary HRI applications that can transform retail, entertainment, travel, and service business today.**

***Index Terms*—AI, Artificial Intelligence, Human–Robot Interaction, HRI, Retail, Robot, Robotics, Service, Technology, Transformation**

I. INTRODUCTION

An increasing body of academic literature examines the mechanisms underlying the interactions between robots and humans [1]. Studies broadly cover robotic systems, human physiology and psychology, and interactions between robotic systems and humans [1]. human–robot interactions (HRI) is, by nature, a broad topic that attracts people in various disciplines, and each discipline is branched and researched from different perspectives. For example, mechanical, electrical, and computer engineers are mainly focused on the topics of robot design, kinematics, dynamics, modeling, planning, decision, and control, plus enabling technologies—sensors, devices, and algorithms [2]. Computer scientists address the computation and algorithms, machine learning, and artificial intelligence [3]. Neurologists and psychologists investigate human cognition [1, 4-6] and behavior [7] to model how social intelligence, emotions, appearance, and personality influence HRI [6, 8]. Recent research seeks to close the emotional distance between humans and robots via physical appearance and emotion-laden social communication [8-10].

Nonetheless, few studies discuss applications of robotic technology to benefit retail businesses [11]. A robot is an individual and automated agent that can freely communicate with customers, meet their needs, offer recommendations, analyze purchase patterns, act on demographic information, conduct real-time inventories, and identify changes in the marketplace [9]. Autonomous robots offer unique, higher-quality shopping experiences [8, 9] that can transform shopping, entertainment, and travel.

This study reviews HRI technologies that facilitate the use of efficient and appropriate retail service robots. It provides business decision-makers with important information about retail innovation technology.

II. HUMAN-ROBOT INTERACTION

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

A. *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 communicate directly or indirectly in the same place and time [9]. Examples of proximate interaction are robotic toys and mechanisms that operate autonomously or are guided by nearby humans [11, 14].

Remote interactions are spatially or temporally separated (Fig. 1). Teleoperation is an example, although interactions in extreme conditions; for example, disaster relief, deep sea operations, or high-altitude and long-range unmanned aerial vehicles, are best known for their

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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].

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

B. Level of Autonomy (LOA)

The level of autonomy (LOA) is a human-centered application in the concept of autonomy. LOA describes the degree of autonomy at which the robot can perform human functions. Many descriptions of LOA have been defined and summarized in the literature, but the most widely cited one is by Tom Sheridan [2]. In that paper, there is a continuum from the completely controlled or operated human level to the fully autonomous agent that does not require input or approval of its actions from a human. The summary of LOA by Sheridan is as follows:

- Computer offers no assistance; human does it all.
- Computer offers a complete set of action alternatives.
- Computer narrows the selection down to a few choices.
- Computer suggests a single action.
- Computer executes that action if human approves.
- Computer allows the human limited time to veto before automatic execution.
- Computer executes automatically then necessarily informs the human.
- Computer informs human after automatic execution only if human asks.
- Computer informs human after automatic execution only if it decides too.
- Computer decides everything and acts autonomously, ignoring the human.

C. Human Signals

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

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], 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 nonlinear 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 extensive data and machine learning processes (Fig. 2 and 3).

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

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

2) Faces

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] (Fig. 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, and influence of external conditions) than numbers and letters in static and dynamic contexts [36]. Impediments to retail applications include systems' mechanical and mathematical sophistication, dependence on image quality, need for learning algorithms, and environmental limitations.

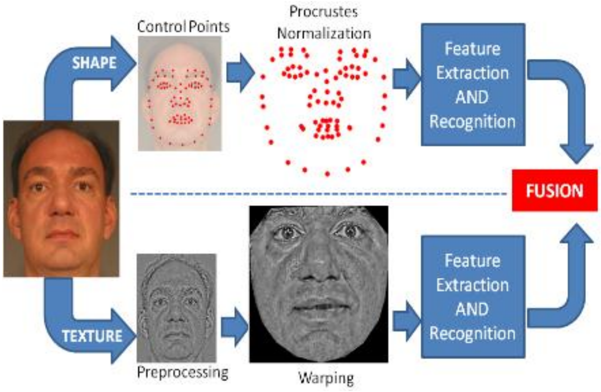

Figure 4. Face recognition process diagram (CMU photo) and a captured image [40]

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 some difficulties afflict this technology, such as complex and changing backgrounds, variable light conditions, deformities of the human hand, and real-time execution dependent on users and devices (Fig. 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].

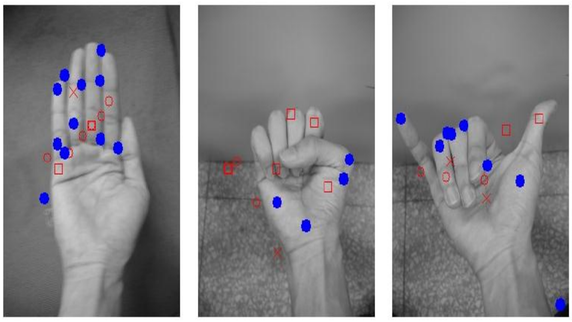

Figure 5. Images of hand gestures and feature extraction [43]; [46]

4) *Speech and voice*

Initiated in the 1950s, speech recognition was adapted to HRI as early as 1970 [47] (Fig. 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].

Figure 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].

5) *Sensors*

Robots need sensors to receive data from human operators or their operating environment. There are many sensors already implemented in robots but those 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 that 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.

6) *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 to 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 (Fig. 7 and 8). Bipedal robots resemble humans and use assorted modes of mobility. Drones or aerial vehicles are used for delivery, rescue, and surveillance.

(a) Mars Rover by NASA

(b) Toyota DJ robot

(c) Google's unmanned car

Figure 7. A picture courtesy by (a) Mars Rover by NASA, (b) Toyota DJ robot and (c) Google's unmanned car.

(a) Honda Asimo robot (b) Amazon delivery drone

Figure 8. (a) Honda Asimo Humanoid robot [60]

(b) Amazon delivery drone

7) *Human-Robot interaction system*

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.

Figure 9. Pepper service robot from Softbank

III. CONCLUSION

This study extends the current literature of robot technologies to retail business and service industry application. Comprehensive studies from the early 1990s to as recently as 2015 have been carefully selected and summarized. We explain the prevailing use-cases of HRI and robotics technologies and their potential uses in retail and service fields. HRI is one of the unique system technologies that requires communication and interaction between humans and robots. In this study, we categorize HRI technologies into 1) proximity, 2) level of autonomy, and 3) human signals. Human signals, the third category of HRI, are classified into seven different types: 1) electromyography, 2) faces, 3) fingers and hands, 4) speech and voice, 5) sensors, 6) robot platform, and 7) systems. This paper is intended to inform non-engineering and retail-technology research groups about the status and transformation of interactive technologies. Further, this paper contributes to the development of retail service robots and their commercialization in service business sectors. We present how robots and HRI technologies could improve customers' service experience and operational efficiency in retail industries. A fruitful extension of this research would be to examine more specific aspects of service robotics, such as social signals, cultivation of trust, and the addition or modification of interactive features that improve HRI and consumer communication with robots.

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