Multisensory Evaluation of Human-Robot Interaction in Retail Stores – The Effect of Mobile Cobots on Individuals' Physical and Neurophysiological Responses

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ABSTRACT

As more mobile collaborative robots (cobots) are being deployed in domestic environments, it is necessary to ensure safety while interacting with humans. To this end, a better understanding of individuals' physical and neurophysiological responses (i.e., short term adaptation) during those interactions becomes crucial to frame the cobot's behavioral and control algorithms. The primary objective of this study was to assess individuals' physical and neurophysiological responses to the mobile cobot in a retail environment. Eight participants were recruited to complete typical grocery shopping tasks (i.e., cart pushing, item picking, and item sorting) with and without a mobile robot running in the same space. Results showed the co-existence of mobile cobot in the retail environment stimulated individuals' physical responses, by significantly changing their upper-limb kinematics, i.e., reducing the average flexion angles of L5/S1 (lower back), T12/L1 (middle back), and right shoulder in the sagittal plane. However, no significant differences were observed in the neurophysiological adaptation based on the measures of muscle activity of the latissimus dorsi, anterior deltoid, and bicep brachii, nor the pupil diameter.

CCS CONCEPTS

• Applied computing → **Physical sciences and engineering** • Human-centered computing → Human computer interaction (HCI) → HCI design and evaluation methods → **Laboratory experiments**

HRI '23 Companion, March 13–16, 2023, Stockholm, Sweden

ACM ISBN 978-1-4503-9970-8/23/03…$15.00
https://doi.org/10.1145/3568294.3580115

KEYWORDS

Human-Robot Interaction, Physical Adaptation, Neurophysiological Adaptation, Retail Environment

ACM Reference Format

Yue Luo, Yuhao Chen, and Boyi Hu. 2023. Multisensory Evaluation of Human-Robot Interaction in Retail Stores – The Effect of Mobile Cobots on Individuals' Physical and Neurophysiological Responses. *In the Companion of ACM/IEEE International Conference on Human-Robot Interaction (HRI'23 Companion), March 13-16, 2023, Stockholm, Sweden.* ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3568294.3580115

1 INTRODUCTION

In 2021, the global industrial robot market was valued at around 43.8 billion U.S. dollars. The market is anticipated to increase at a nearly 10% compound annual growth rate by 2028 and will be worth close to $70.6 billion U.S. dollars [1], Industrial robots are becoming more and more widespread in the workplace, particularly in industries like agriculture [2], manufacturing [3], healthcare [4] and customer service [5]. The market for industrial robots has grown, and their deployment formats have evolved as well. Traditionally, robots are physically isolated from human workers for safety concerns, which has limited their use in industries that require frequent and direct interactions between humans and robots. As a result, collaborative robots (cobots), a new form of robotic automation designed to work safely alongside human workers, emerge as a viable option. In industrial examples such as wholesale and retail trade (WRT) [6], [7], cobots are deployed to take over repetitive and tedious tasks (e.g., cleaning, disinfection, inspection, and delivery), freeing up human workers to focus on tasks that require advanced environment perception, decision-making, and/or object manipulation that are beyond the capability of current robotic technologies [8], [9]. While cobots are intended to complement human workers and increase the overall system efficiency, it is crucial to assure their safety by correctly perceiving and predicting how people respond to them in a shared space. Previous literature has focused on the psychological aspects involved in human-robot interaction (HRI), such as acceptance [10] and trust [11], to calibrate humans' perception of advanced technologies. In this study, we aimed to further expanding our knowledge base by investigating not only individuals' neurophysiological but also their physical responses (i.e., short term adaptation) to mobile cobots that work closely with humans in the WRT environment. By including individuals' neurophysiological and physical responses, human behavior can be better quantified or even predicted. benefiting an efficient and effective interaction between human and cobots. The research question and hypotheses are constructed as follows:

Research Question: What effect does the presence of the mobile cobot have on individuals' physical and neurophysiological adaptation in the retail environment?

Research Hypothesis 1: The presence of the mobile cobot can alter individuals' physical behavior in the retail environment, as indicated by their upper-limb kinematics measures.

Research Hypothesis 2: The presence of the mobile cobot can alter individuals' neurophysiological behavior in the retail environment, as indicated by their muscle activities and pupillary response measures.

2 METHODS

2.1 Participants

Eight participants, three females and five males, were recruited from the university student population to participate in this experiment. Their mean (SD) age and height were 19.4 (2.0) years and 176.7 (10.2) cm. All participants reported being healthy, with no recent musculoskeletal problems requiring medical attention. One participant claimed to be ambidextrous, while the others claimed to be right-handed. The University of Florida Institutional Review Board authorized this study (IRB202002765).

2.2 System Setup

2.2.1 Experiment site: The experiment was conducted in a high-fidelity retail environment (Figure 1). The facility is equipped with movable shelves and essential accessories such as a checkout machine, a shopping cart, and over 100 common grocery items.

2.2.2 Robot platform: The retail robot used in the experiment consisted of a Fetch Freight Base (Fetch Robotics, Inc., San Jose, California) and a UR5 robot manipulator (Universal Robots, Odense, Denmark) as shown in Figure 1. The robot is 1.295 meters tall and has a 0.508 by 0.559 meter footprint. The robot had a 2D LiDAR sensor, a webcam, a 6D inertial measurement unit (IMU) sensor, and two wheel-encoders. It was controlled by the Robot Operating System (ROS) with an Intel i3 CPU, an 8 GB RAM, and a 120 GB SSD. Using the same control scheme as in our earlier experiments [7], the robot was programmed to travel between predefined waypoints with the capacity of obstacle avoidance and path re-planning. During the experiment, the robot's maximum moving speed was set at 1.0 m/s, while the UR5 remained deactivated and retractable.

2.2.3 Motion capture system: The IMU-based motion capture system Xsens (MVN Awinda, Xsens Technologies BV, Enschede, Netherlands) was used to record participants' positions and body postures during the experiment to overcome the marker occlusion issue that arises in camera-based motion capture systems. The system consists of a total of seventeen IMU sensors (~ 10 g per sensor) that can be affixed to the top of participants' outfits in accordance with the manufacturer's instructions [12]. The sampling frequency of the system was 60 Hz.

2.2.4 Electromyography system: Muscle activities were recorded using the surface electromyography (EMG) system (Delsys Trigno, Delsys Inc., Boston, MA). Each wireless EMG sensor has four silver bar electrodes and an integrated amplifier. The muscle groups, i.e., latissimus dorsi, anterior deltoid, and bicep brachii on the right side of participants were selected and the sensors were attached to them using double-sided adhesive tape with no electrode gel required. The maximal voluntary contraction (MVC) of these muscles was measured with reference to [13].

2.2.5 Eye tracking system: A head-worn eye tracker, Tobii Pro Glasses 2 (Tobii, Danderyd Municipality, Sweden), was utilized to record pupil diameter, which is a sensitive physiological indicator of cognitive workload [14]. Appropriate corrective lenses were snapped on if needed. The sampling frequency of the eye tracker was set at 50 Hz.

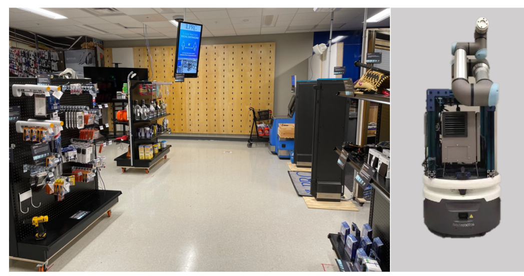

Figure 1: Experiment site and robot platform.

2.3 Experimental Design

A within-subject experiment was designed to evaluate the effect of the robot on individuals' physical and neurophysiological adaptation in the retail environment. The independent variable was the robot condition, i.e., "no robot" and "with robot". The dependent variables included measures that depict the physical (i.e., body kinematics) and neurophysiological (i.e., muscle activity and pupillary response) responses of each participant. During the experiment, participants were instructed to complete ten grocery shopping tasks with (#:5) and without (#:5) the retail robot. The grocery shopping task was designed as a series of continuous actions, which included: (1) pushing a shopping cart between shelves, i.e., cart pushing task, (2) scanning and picking eight items, one from each shelf, i.e., item picking task, and (3) sorting the items into two bins at the checkout machine, i.e., item sorting task) (Figure 2). At the beginning of each trial, a list including all the items of the target was given to the participants. And the participants were asked to pick up items in the correct sequence using their right hand. During the trials in which the participants performed the grocery shopping tasks alongside the mobile robot (i.e., the "with robot" condition), the retail robot was designed to circle the "store", representing a platform realizing functions, such as disinfection, cleaning, and inventory management in retail environments. The waypoints of the robot were illustrated in Figure 2. The order of the robot condition was presented at random to prevent systematic errors and potential learning effects.

2.4 Procedures

Upon arrival, participants first consented to participate in the study and provided their demographic information including their gender, age, height (with shoes on), and handedness. Following that, three EMG sensors were placed on the right side of the latissimus dorsi, anterior deltoid, and bicep brachii muscles. MVC for each muscle was then tested following the guideline [13]. After the MVC trials, motion capture sensors and the eye tracker were attached to the participant's body and both systems were calibrated. Ten grocery shopping tasks were subsequently given to the participants, five “with robot” and five “without robot”. To prevent fatigue, a mandatory rest of at least 2 mins was designed between each trial.

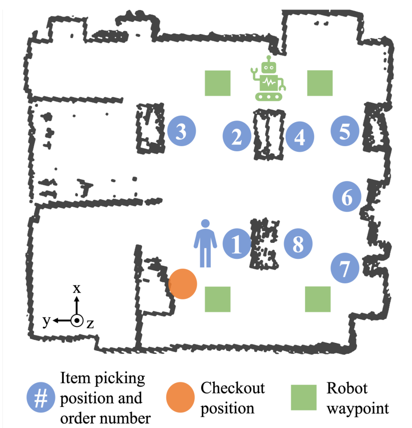

Figure 2: The SLAM map of the experiment site and illustrations of participants’ grocery shopping tasks as well as the robot’s path to circle the store.

2.5 Data Analysis

This study focused on participants' upper limbs since the tasks designed for the experiment (e.g., picking and sorting items) required a lot of movement in that region. Participants’ physical response data is their kinematics captured by the motion capture system, to indicate participants’ motor adaptation to perturbations [15]. The average joint flexion angle of L5/S1, T12/L1, Head/C1, and right shoulder in the sagittal plane were calculated using custom MATLAB code [12] after loading the raw joint angle exported from the software, MVN Analyze (Xsens Technologies BV, Enschede, The Netherlands). The neurophysiological measures contain muscle activity from the EMG system [16] and pupillary responses [17] from the eye-tracking system. Muscle activity represents the levels of muscle activation for the upper body and it was calculated from the EMG signals normalized by participants’ MVC, after steps of: 1) mean removal, 2) bandpass filter (4th order Butterworth, 20-500 Hz), 3) absolute value acquisition, and 4) root mean square calculation (window length 300ms, no overlaps) following [18]. The pupillary responses were depicted by calculating the average pupil diameter for each trial, by pooling the left and right sides of pupil diameter together.

2.6 Statistical Analysis

One-way repeated ANOVAs were conducted using R studio (R version 3.6.0), with the robot condition as the independent variables, measures of upper-limb kinematics, muscle activity, and pupillary responses being the dependent variables. The assumptions of the model (normality & homogeneity of variance) were visually checked. Although moderate deviations from normality were noted, ANOVAs were reported to be robust to these discrepancies [19]. During the analysis, participants were treated as the random effect. The significance level of $\alpha = 0.05$ was used across all tests.

3 RESULTS AND DISCUSSION

3.1 Upper-limb Kinematics

The significant difference in the upper-limb kinematics measures under two robot conditions revealed the effect of a robot on individuals’ physical adaptation. As shown in Table I, when compared to the “no robot” condition, the “with robot” condition induced a decrease in joint flexion angle of L5/S1 (4.80 vs. 4.14 degrees, $F(1,68) = 4.23$, $p = 0.044$), T12/L1 (2.13 vs. 1.84 degrees, $F(1,68) = 4.10$, $p = 0.047$), and right shoulder (25.06 vs. 22.42 degrees, $F(1,68) = 9.84$, $p = 0.003$). No significant changes were observed in terms of Head/C1 flexion angle between conditions.

Participants were found to flex less of their trunk (i.e., L5/S1 & T12/L1) and their shoulder throughout the trial, indicating a more erect standing posture with the presence of a robot in the retail environment. One of the reasons for the adaptation of an erect

TABLE I. MEAN (STANDARD DEVIATION) OF TEN PARAMETERS AND THE EFFECT OF ROBOT CONDITION ON THESE PARAMETERS.

Parameters		Robot Conditions		
		No Robot	With Robot	*p*-value
Upper Lib Kinematics – Average Flexion Angle (degrees)	L5/S1	**4.80 (4.43)**	**4.14 (5.06)**	**0.044**
	T12/L1	**2.13 (1.97)**	**1.84 (2.25)**	**0.047**
	Head/C1	-0.81 (6.21)	0.10 (8.00)	0.354
	Right Shoulder	**25.06 (7.09)**	**22.42 (7.60)**	**0.003**
Muscle Activity – % Activation (%)	Latissimus Dorsi	5.33 (3.89)	5.15 (3.60)	0.823
	Anterior Deltoid	4.91 (2.54)	4.89 (2.92)	0.543
	Bicep Brachii	4.26 (4.95)	3.96 (4.7)	0.406
Pupillary Responses (mm)	Pupil diameter (L & R)	4.35 (0.25)	4.34 (0.26)	0.632

standing posture during the HRI can be the participants' unintentional effort to minimize their physical footprint in the environment, minimizing potential collisions with the retail robot, and ensuring timely responses to the unexpected actions executed by the retail robot.

3.2 Muscle Activity

There was no significant difference found in the levels of muscle activation of the latissimus dorsi, anterior deltoid, and bicep brachii muscles between two robot conditions (Table I). Overall, the three muscles that are evaluated had low levels of muscle activation (less than 10%), which is expected as normal retail tasks that do not generate intense short-term muscle strains. The presence of a robot did not lead to muscle activity changes in the three muscles. According to 3.1, the reduction in the right shoulder flexion angles may be related to the changes in the activation level of other muscle groups, for example, pectoralis major and coracobrachialis [20], rather than the anterior deltoid. Also, it might be the case that the co-existence of a mobile cobot could strongly influence personal physical behavior at some critical moments (e.g., when the two agents interact or surpass) and their EMG patterns, but not so at the whole trial level. In order to investigate this, we plan to conduct more detailed analysis with a higher resolution and sensitivity.

3.3 Pupillary Response

In terms of pupillary responses caused by the robot, no significant difference was found in the pupil diameter measure between "with robot" and "no robot" conditions. Pupil diameter is commonly regarded as a physiological measure of an individual's cognitive workload, which tends to increase as the workload increases [14]. Although no difference was observed in the pupil diameter in this experiment, our previous research efforts have shown that participants' workload was negatively affected when they were interacting with a robot in the WRT environments [7], [21]. The conflict in results is probably due to different sets of tasks designed in the human-robot interaction environment. Further follow-up studies can take this into consideration and investigate individuals' pupillary response to robots while they were performing tasks at varied engagement levels.

ACKNOWLEDGMENTS

The authors gratefully acknowledge the support of the National Science Foundation-USA under grant # 2132936. Any opinions, findings, conclusions, and/or recommendations expressed in this material are those of the authors and do not necessarily reflect the view of the National Science Foundation.

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