Influence of Size-Weight Illusion on Usability in Haptic Human-Robot Collaboration

Jonas Schmidtler, *Graduate Student Member, IEEE* and Klaus Bengler

Abstract—Collaborative power amplifying robots are accepted as one solution to overcome flexibility and ergonomic issues in future work and life scenarios. Handling of various sized and weighted objects in heterogeneous environments pose a particular challenge to the often applied admittance control. Haptic illusions, especially the Size-Weight Illusion (SWI), where the smaller of two equally weighted objects is perceived to be heavier, can have malicious, disturbing or to some extent useful influence on system stability and usability. A within-subjects experiment was conducted with 40 participants and three within-factors (size weight, and movement type), to investigate the occurrence and influence of SWI in bimanual fast-imprecise and slow-precise planar manipulation tasks. The illusion was replicated and an influence on usability was found. Further, different control strategies according to object size and mass (static, compensatory, and mismatch) were analyzed and did not show significant effects on task performance. It appears that either no change in assistance or a change according to object size is advisable.

Index Terms—Human factors, human-robot collaboration, size-weight illusion, usability, admittance control

1 Introduction

HUMAN-ROBOT INTERACTION is currently growing stronger in relevance than ever and is increasingly merging into many areas of work and life. Novel interaction concepts are to serve current social and industrial developments by utilizing the strength and potential of each partner. These endeavors involve domains like rehabilitation, prosthetics, health care, surgery, space, military, agriculture, education, household, industry, and physical work in general [1]. A promising approach lies in the close complementary haptic collaboration between humans and robots. It is possible to compensate weaknesses of each partner by strengths of the other, by using robotic capabilities like power assist, inertia masking, and virtual guidance [2], [3] and combine them with the human high fidelity sensory system within a shared control approach [4], [5]. Increasing diverse human capabilities and characteristics, caused by an ongoing demographic change [6], [7], require adapted solutions to ensure optimal usability, enable health-preserving applications, and eliminate musculoskeletal disorders. Individuality and flexibility are now spreading throughout all areas of work and life, as apparent in today's trends such as the so-called mass customization of services and products [8]. These involve tremendous amounts of flexibility in new production systems, which have to include the human in hybrid systems to meet the challenges of complexity and uncertainty [9]. According to [1], all robots will, in some way, still be controlled by humans for the foreseeable future. Close and direct physical collaboration (in contrast to telemanipulation) of human and robot for strength amplification, is speeded up by new standards [10], [11] and a rapid progression of novel robotic systems [12], [13].

The objective of this article follows the design approach of human-centered assistance applications (HCAA, [9]), which focusses not only on the robotic side, but concentrates specifically on the characteristics and idiosyncrasies of the human operator. Based on a very well-known haptic illusion, called the Size-Weight Illusion (SWI) [14], where the smaller of two equally heavy objects is perceived as the heavier one, and the results in [15], a study was conducted to investigate the effects of different object sizes and control strategies on usability of novel intelligent assist devices (IADs).

2 State of the Art

2.1 Haptic Human-Robot Collaboration

Haptic Human-Robot Collaboration (hHRC) [16], a part of physical Human-Robot Interaction [17], is defined as the interaction of human and robot in the same workspace, at the same time, with a common goal, and physical haptic contact [9]. The main goal of this interaction concept is to eliminate weaknesses of one partner with the strength of the other [17], [18], like the flexible adaptability of humans and power of robots [13], [19]. According to [20], hHRC can be distinguished in joint object manipulation and collaboration without an object (e.g. programming by demonstration, rehabilitation, and surgery). The focus of this article will be on the first category targeting e.g. automotive assembly lines with a wide range of different object sizes and payloads. Robotic human strength amplifying systems are developed under the names of Cobots (collaborating robots [2], [3]), IADs

• *J. Schmidtler and K. Bengler are with the Chair of Ergonomics, Technical University of Munich, Garching, BY 85747 Germany.*
E-mail: {jonas.schmidtler, bengler}@tum.de.

Manuscript received XX; revised XX; accepted XX. Date of publication XX; date of current version XX.
Recommended for acceptance by XX
For information on obtaining reprints of this article, please send e-mail to: reprints@ieee.org, and reference the Digital Object Identifier below. Digital Object Identifier no. XX

(intelligent assist devices [21], [22]), PARS (power assist robot systems [23]), and exoskeletons [24].

Most of these applications use admittance controllers, where a force-torque sensor detects the human intentions over a handle, directly over the payload, or by torque sensors and motor current feedback in the joints of robotic devices [25], [26]. These controllers measure force as an input and translate this information into displacement [22], [27]. The admittance equation in one dimension (1), which basically represents a mass-spring-damper system, is defined by the interaction force F_H that is applied by the human operator, the virtual target mass m_t, the virtual target damping c_t, and the virtual target stiffness k_t. Additionally x_0 is the starting point and x, $\dot{x}$, and $\ddot{x}$ are position, velocity, and acceleration.

$$F_H = m_t(\ddot{x} - \ddot{x}_0) + c_t(\dot{x} - \dot{x}_0) + k_t(x - x_0) \qquad (1)$$

In the following, only free motion will be considered. Hence, stiffness k_t as well as the position x_0 are set to zero, which rewrites the admittance equation as:

$$F_H = m_t\ddot{x} + c_t\dot{x} \qquad (2)$$

This translates into the relationship that when the admittance parameters (mass m_t and damping c_t) are set to high values, a larger human interaction force F_H is required to move the robot at a certain velocity and/or acceleration [22]. As [22], [28], [29] point out, it is easier to manipulate the robot in fast-imprecise motions with lower and in slow-precise motions with higher admittance parameters. As [22] adds, variable admittance control allows to adjust these parameters to inferred human intentions and as [15] follows, this could be complemented by a Bayesian framework to integrate two or more human sensory inputs. In terms of manual object manipulation, the visual and the somatosensory system are the dominant sensory systems of the human to initialize and perceive movements. In the following, a brief overview of human motor control and haptic illusions caused by object characteristics is given, in order to present the applied control strategies.

2.2 Haptic Illusions and their Effects on Haptic Human-Robot Collaboration

2.2.1 Human Motor Control and Sensory Integration

Analog to robots, the human motor control can be categorized in controller (the central nervous system, CNS), actuators (muscles), and sensors (proprioceptors) [30]. The presented study will focus on haptic interaction, specifically on kinesthetic or proprioception, which are, besides the cutaneous sense, parts of the human somatosensory and motor system [31]. They provide the human with the ability to sense the position and motion of body and limbs [32]. Mechanoreceptors or proprioceptors in the human vestibular system, skin, joints, muscles, and tendons provide us with the ability to be aware of movements, spatial orientation, and forces. Signals are sent over the spinal cord and nerve fibers in the medical lemniscal pathway to higher levels of the CNS, represented by the somatosensory cortex. Muscle spindles and Golgi Tendon Organs are able to additionally transmit the position and force information of muscles to the α-motoneuron and enable fast feedback loops (spinal reflexes) [30].

The human motor system is not constant in its properties, it adapts to plan future movements based among others on sensory integration [33], motor learning [34], and motor control of our internal forward models [35]. To move an object, the human motor system has to predict its mass and anticipate appropriate forces. Problems can arise when this prediction is erroneous, i.e. if the information stemming from prior-knowledge (top-down) does not match the perceived stimuli (bottom-up). A commonly used example in this context is a cup of water. Imagine you grab the cup, looking like it is made out of glass, but by touching and lifting it, realize that it is actually made out of plastic, only glass-looking, and apparently weighing less than you expected. The surprising effect is even greater, if you do not know how much and what is inside the cup (e.g. if the cup is opaque). Now if you transfer this example to hHRC, analog issues arise. The human operator is, to some extent, unaware of the admittance parameters (1, and 2) that the power amplifying robot will present, but s/he can visually perceive the object that has to be manipulated (in some cases, applying the so-called *hands-on payload* mode, even haptic information about the object will be derived). This visual (and haptic) stimulus will address existing (prior) knowledge [36], [37] about the object (e.g. a huge metal looking object will/should be heavy). In the next step, the human will initiate the manipulation and receive, besides the visual information, proprioceptive stimuli (e.g. the robot displays the human an inertial target mass m_t = 5 kg and low damping values c_t). During this step, sensory integration will report that there is a mismatch between top-down and bottom-up information, which can lead to accidental misuse by applying inadequate forces.

2.2.2 Haptic Illusions

Literature tells us that variations in object properties that are not directly related to weight can influence perceived heaviness and can thereby be considered as illusions [38]. According to [39], illusions are “the marked and often surprising discrepancy between a physical stimulus and its corresponding percept”. Lederman and Jones [39] gave a holistic overview of haptic illusions of objects and their properties with respect to tactile/haptic processing of material (texture, stiffness, temperature), geometry (size, shape), and the hybrid attribute of weight, that is influenced by both material and geometric properties. In this article, we will focus especially on perceived weight (more precise: inertial mass) and its interdependence with size, the so-called Size-Weight Illusion (SWI).

The strong and robust Size-Weight Illusion [40] was already found in 1891 by the French physician Augustin Charpentier [14]. This psychophysical finding describes

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TOH.2017.2757925, IEEE Transactions on Haptics

the effect that when lifting two equally weighted – but different sized – objects, the smaller is generally perceived to be heavier. Theories on the caused mechanism range from concepts of perceptual sets or expectation [41] (described in the example) to modality based ones that emphasize the importance of sensory information [42]. The latter one explains the strong effect of modality on SWI that is used to perceive the object. Ellis and Lederman [42] found that with haptic information, strength of the illusion is highest and significantly weaker when volumetric cues are sensed only visually. They follow that these findings indicate the necessity of haptic volumetric information to produce a SWI. This is contradicted by the study of Schmidtler and Bengler [15] (and the presented study in this article) that found evidence for SWI in visual object size perception only conditions as well. Fundamental studies of Stevens and Rubin [43] and Amazeen and Turvey [44] indicate a function of perceived heaviness and volume of an object. This was continued by Cross and Rotkin [45] who were able to find power functions converging in the proximity of the heaviest weight that can be lifted. Also other illusions that influence the perceived weight can be named (like Material- or Density-, Shape-, Surface Texture-, Temperature-, Color- and expert-related Weight-Illusions like the Golf-Ball-Weight Illusion), but will not be subject of the subsequent investigations. It also has to be mentioned that all these other weight-illusions are weaker than the traditional SWI. For further, information consider the review of [39] and [46].

2.2.3 Effect on Haptic Human-Robot Collaboration

The consulted literature about SWI focuses only on lifting movements, of small, light-weight objects involving only few limbs and muscles, applying small forces. Only one example was found (besides the authors' work [15]) of horizontal manipulation, where different sized objects where pushed using a long pendulum [47]. This study showed that the inertial mass (besides its gravitational) also provokes a robust and strong SWI. In terms of object mass only two exceptions could have been found that addresses masses in the kilogram range. Buckingham et al. [48] used fitness barbells with 2.3 kg and 4.5 kg and Luebbers et al. [49] with 97.5 kg and 102.1 kg to investigate whether SWI has a measurable influence on performance in weight training, but did not find such an effect. Since the authors could have shown that object size related sensorimotor prediction appears in imprecise bimanual manipulations, with high masses (40 kg) [15], but did not find complete conclusive subjective results, it was of interest if this effect has an influence on the usability of haptic collaborating robots. No exemplary study was found that investigates SWI related concepts to the field of robotics. Analysis conducted by Rahman, Ikeura, and colleagues in the years between 2008 and 2012 (e.g. [50]) are the only studies close to the topic of influencing object characteristics in hHRC. Again they used small objects (of about 13 g) and very short lifting movements. To ensure high quality and performance of manipulation tasks, knowledge about the human handling of different sized objects with adaptive power assistance is mandatory. Size-Weight Illusion occurs, but how and should it actually be addressed in the design, control, and operation of novel intelligent assistance applications?

3 Objectives

3.1 Control Strategies – Chance, Challenge, or Nuisance

A power assisting collaborative device will take load of the human by amplifying his/her power [2], [3], [22], [26]. Current systems do not take into account size cues and the inevitable consequence that novel heavy-looking objects will be manipulated with more power than novel light-looking objects [15], [37], [51]. As a consequence, accelerating/decelerating large objects can lead to increased force and force-rates, which can result in instability issues [27]. The proposed solution by [27] is to increase target inertia m_t instead of damping c_t, because they found out that it creates much less deterioration in the required operator effort than target damping, which was used so far to ensure and increase stability [21]. Since, it is favored that there is no malicious effect on operator effort and the consequent likely lower task performance, it was our goal to investigate the design of different target inertia m_t in the light of object size cues. Therefore, the main question of this article is whether haptic illusions and especially size cues should be considered for the design of physically assisting devices in terms of optimizing their usability and stability at the same time.

The influence of the SWI on hHRC was investigated, in terms of the underlying cognitive processes and usability, as well as to enhance the display of information. We see the potential or *chance* to overcome stability issues and boundaries (e.g. from a robot-centric view see [22], [52]) by skillfully applying haptic illusions. A *challenge* can arise if the interaction of power assistance and object sizes is inappropriate, which could lead to increasing illusion effects and refusal of adaptive collaborative robots (from a human-centric view [9], [15], [51]). If nothing is changed in the control strategy of the haptic device and a conservative admittance control with no adjustments and no adaptive or variable capabilities is applied, SWI will still influence task performance in form of *nuisance*. If these ideas are connected to a hHRC control strategy like the aforementioned variable admittance, the following three control modes are conceivable (see also Fig. 3):

Compensatory (chance): Humans apply higher forces on larger objects, because in general (error-based learning) a larger object is heavier, a smaller object is lighter. Hence in the compensatory mode the admittance parameters of (2) should be higher for larger and lower for smaller objects to compensate for higher force or higher accelerations and hence increase stability of the system.

Static (nuisance): If no adaption of the admittance parameters takes place, the human could learn and get to know the assistance of the system regardless of object sizes. This would, of course, only be possible for a higher number of manipulations [34]. Still, SWI would appear and would have to be eliminated in terms of optimal usability and acceptance of the system.

Mismatch (challenge, control group): If the variable admittance parameters are faulty, due to incorrect settings or system boundaries small objects can appear even heavier than larger ones. This can highly influence task performance and acceptance of the system.

3.2 Hypotheses

The speed-accuracy trade-off tells us that humans can either perform very fast, but imprecise or very precise, but slow [5], [53]. In the conducted study, the use case of an automotive assembly line was applied, where heavy and bulky objects are manipulated using (today) non-actuated handling systems. The above-mentioned trade-offs in movement types can be found in taking a component from outside the line to the installation site, which has to happen fast, and in precise positioning of the part during the assembly (i.e. properly meet drills or notches, which requires high accuracy). The main manipulation type in this area are horizontal push and pull movements. In terms of a smart factory, production and specifically assembly will have increasing demands of flexibility and adaptability. By using novel hHRC devices, a large amount of different sized and weighted parts will have to be manipulated. Hence, today's and future automotive assembly serves as an appropriate example for the following investigations.

Based on this background a study was conducted to investigate the appearance, influence, and assistance strategies in terms of the SWI. The consulted literature, besides the authors' preliminary work [5], [15], [51], did not address bimanual, imprecise, and horizontal manipulation types with focus on whole-body movements. Hence, the first hypothesis should clarify, if SWI occurs in bimanual imprecise-fast and precise-slow horizontal manipulations, with high payloads and power assistance:

H1: Size-Weight Illusion occurs in imprecise-fast and precise-slow bimanual planar manipulation with high payloads.

If SWI takes place, it was of interest, how it may influence usability of the system and therefore task performance. Hence, the second hypothesis reads as follows:

H2: Visual object size cues influence the usability of the system.

As a consequence, if the SWI influences usability and task performance, the focus of the following analysis was, to find the optimal assistance strategy in terms of different movement types, object sizes, and payloads.

H3: The assistance strategy influences usability of the system.

4 Method

4.1 Sample

An a priori power analysis using G*Power [54] for a repeated-measures ANOVA with three within-factors was performed to justify sample size. Since we expected medium to high effects, based on the results in [15], we used $\eta^2 = 0.07$, aimed for a power of 0.95, and a significance level of $\alpha = 0.05$, which resulted in a suggested total sample size of 30 participants. Hence, we recruited 40 participants (15 f, 25 m) to take part in the study. The mean age of the sample was 25.8 years (SD = 3.1) and ranged from 20 to 32 years of age. The sample's age is homogenous and relatively young, with respect to a factory worker population, but has the advantage of almost no age-related physical and perceptual interference with the task [55]. Anthropometric measurements for body height (M = 178.1 cm, SD = 8.8 cm, 15. p* woman–98. p man; *percentile) and body weight (M = 71.1 kg, SD = 13.1 kg, 4. p woman–92. p man) in relation to the age-group from 18–65 years of the SizeGERMANY survey [56], indicate representative anthropometrics of the German population. No participant reported any motoric or sensory impairment that could interfere with the experimental tasks.

4.2 Experimental Setup

The study was conducted in a laboratory at the Chair of Ergonomics at the Technical University of Munich. A manually operated manipulator (manufactured and installed by eepos GmbH ©; Fig. 1) was used to carry three different sized objects, *small* (1500×1000×40 mm), *medium* (1500×1000×200 mm), and *large* (1500×1000×400 mm), by means of four vacuum cups (Fig. 1). The objects are made out of Styrofoam, covered by opaque paper and a white wooden panel on top. In combination with the eepos low friction rails, hinge trolleys, and an electro-mechanical lifting axis gravitational masses were nearly eliminated. Including all attached parts (without an object and additional weights) the inertial mass in the x-axis was 389 kg and y-axis 186 kg (coordinate system in Fig. 2). Hidden weights, mounted on the system, were used to simulate different target inertia masses m_t, creating three *weight* conditions (0, 50, 100 kg additional mass) and balancing the three different sized objects to weigh exactly the same. The operator was able to manipulate the system via vertically oriented handles. They were adjusted in height (90° elbow angle) and width (5–10° between elbow and torso) to fit each individual's anthropometric requirements [57].

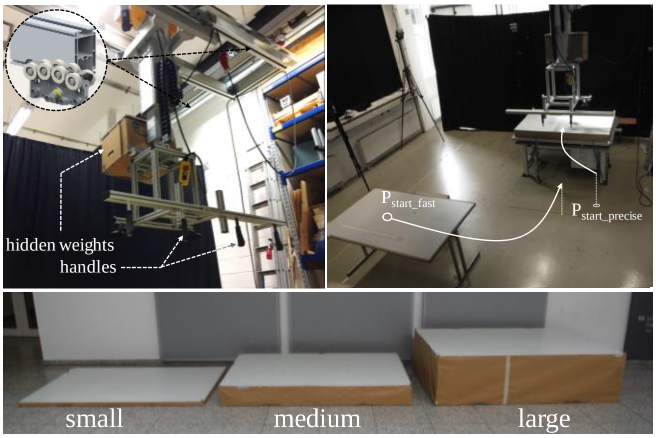

Fig. 1. (Left) Manual manipulator–eepos double girder crane system including a perpendicular railing system and an electromechanical lifting axis; (Right) Experimental setup. (Bottom) Three different sized, but equally looking, objects. Please also have a look at the supplementary video files.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TOH.2017.2757925, IEEE Transactions on Haptics

Fig. 2 shows the experimental setup from a bird's-eye perspective. The positioning location was realized with an electromechanic height-adjustable table, which was adapted according to each participant's anthropometric demand, to prevent disturbance because of visibility of the positioning area or the like (Fig. 1). To simulate a positioning task, a frame was built from MayTec aluminum profiles and mounted on the positioning table that represented the plane measurements of the used objects. In that way it was possible to insert each object into this frame and create a task close to an automotive assembly use-case. Ten Vicon Motion Capturing cameras were used to track the participants' as well as the manipulator's movements (at 100 Hz). The Vicon Nexus software was used for pre-processing of the position data. If the damping c_t of (2) is neglected, the human force input F_H can be rewritten as:

$$F_H = m_t \ddot{x} \tag{3}$$

With this simplification it was possible to estimate the human interaction force out of the motion tracking data.

4.3 Procedure

The experimental design consisted of three within-subject factors *size* (small, large), *weight* (0, 50, 100 kg) and *movement type* (fast, precise). By randomizing the *movement type* order two groups evolved. The fast-precise group consisted of 20 participants (7 f, 13 m) and completed the full task of imprecise-fast bringing followed by precise-slow positioning. The precise-fast group consisted of 20 participants (8 f, 12 m) and experienced the task the other way around. Fig. 3 depicts an exemplary experimental procedure, consisting of three different assistance strategies called *control strategies*, which were randomized for each participant to avoid order and learning effects. The *control strategies* were designed according to the control strategies described in 3.1. The approach should clarify if there is a need to adapt virtual target mass m_t of the admittance control (1–3) to the expected higher/lower mass of larger/smaller objects. Hence, the control strategies are called *static*, for no adapting of masses relative to object size, *compensatory*, which should adapt accordingly to the expected higher/lower mass of larger/smaller objects, and *mismatch*, which represents a control condition with an opposite and unexpected relation of size and weight. Novel power assisting devices will only be used and accepted, if humans are able to manipulate a variety of objects in a safe and efficient manner. As a consequence, if many different objects are manipulated, it can be the case that weight illusions take place, because of sequential order of different sized and weighted objects. By applying a defined order of object sizes (M-L-S-L, see Fig. 3.) starting with a reference object (M), followed by a larger object (L), each participant was initially primed in terms of sensory motor memory to a new object-size-weight combination as well as a standardized object size difference. Because the proportion of larger objects manipulated with power assist devices will be greater than of smaller objects, it was decided to use a large object (L) as priming condition.

Before the experiment, the participants filled out a demographic questionnaire, anthropometric measurements were taken, and VICON markers were attached. Introductory videos were used to inform the sample about the procedure, the different movement types (fast-imprecise bringing and slow-precise positioning), and the underlying use case of an automotive assembly line. In this way, it should be controlled that each participant starts with the same mindset and from the same level of knowledge. Special care was taken to ensure that each participant was unaware of the impending illusions or phenomenon under study. The instructions and questions in the experiment were designed not to lead a subject's answers to the presence or absence of an illusion and provided unbiased answer options (e.g. 100-point strain scale, see 4.4). In that way, influences of the experimental design on perceptual

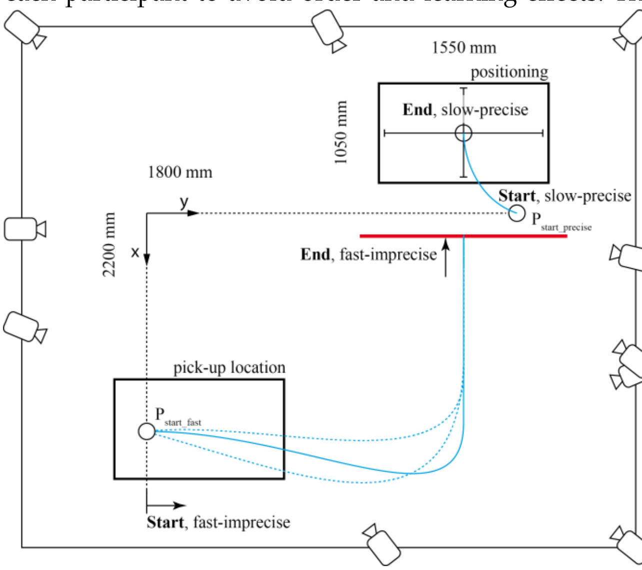

Fig. 2. Experimental setup: Starting with a fast-imprecise movement from the pick-up location (P_{start_fast}) to the first End-position (marked with a red line on the floor); Re-calibration of the system to the Start, slow-precise using a laser-pointer that is fixed on the system and a marker on the floor ($P_{start\_precise}$). Positioning the object on a height-adjustable table and a custom frame that fits the objects face.

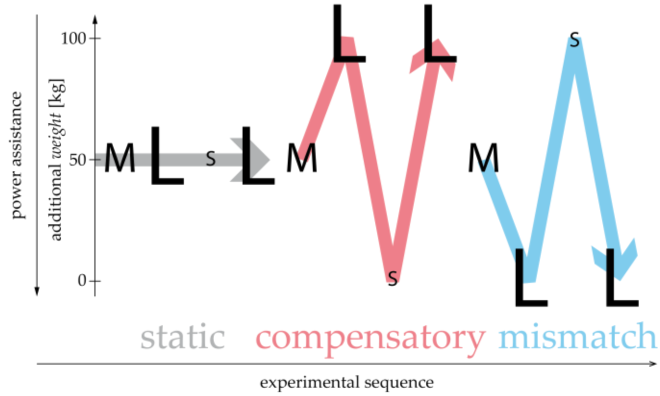

Fig. 3. Experimental procedure: Strategies *static* (black), *compensatory* (red), and *mismatch* (blue) were randomized using Latin square. Conditions were varied using three additional *weights* 0, 50, and 100 kg to simulate different power assistance modes and three different object sizes *small* (S), *medium* (M), and *large* (L).

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TOH.2017.2757925, IEEE Transactions on Haptics

judgments and inflated estimates should have been avoided. After calibrating the motion tracking system to the participants' anthropometrics, they had to execute several initial trials to familiarize with the system and the two different task procedures (bringing, positioning). Fig. 2 shows the two different movement types, based on the use case. As reference condition a medium sized object and 50 kg (50M) was used in this phase.

After filling out the initial questionnaire (asking about attitude and experience with robots) the main experiment with 12 trials (consisting the seven possible combinations shown in Fig. 3) started. The following procedure description applies for the f-p group that started with a fast bringing followed by a precise positioning of the object. The two tasks (*movement types*) were randomized and occurred in reversed order for the p-f group. Starting from P_{start_fast} at the pick-up location the participants moved the system as fast as possible towards the positioning table and were told to stop right before it, marked with a clearly visible red line on the floor. They were distinctly advised not to overshoot this line, because in a real scenario this would mean they would damage the car and the handled object and probably hurt themselves. In the second part, the experimenter positioned the system to a fixed starting point, for the slow-precise part, using an attached laser-pointer and a marking on the floor ($P_{start\_precise}$). The participants were told to position the handled object as accurately as possible to match the underlying frame on the positioning table. As a last step, they used the electro-mechanical lifting axis to assemble the frame with the object. After each trial the participant stepped out of the room, put in ear-plugs (to avoid any acoustic information about changes in the set-up), and filled out a questionnaire (100-point scale, NASA TLX, and self-designed questions about the interaction and overall satisfaction). After completion of all trials, which took around 1.5 hours, the participants filled out a final questionnaire and were compensated with sweets and drinks for their participation.

4.4 Measures

4.4.1 Indices of sensorimotor prediction

We used the first peak load force value ($F_{1stpeak}$) [47] at the initial movement as an index for sensorimotor prediction. This was accomplished using the motion tracking data to obtain the resulting acceleration. Differentiating the position signal after time using a five-point stencil [5], [51], [58] results in a velocity. The velocity signal was smoothed using a 50-Hz Butterworth filter [58]. Again derived and multiplied by the according axis-dependent mass of the system (x = 389 kg, y = 186 kg; see 4.2) results in the acting forces using (3). Since the two different manipulation types fast-imprecise and slow-precise will be analyzed separately, the load force will be named $F_{1stpeak\_fast}$ and $F_{1stpeak\_precsie}$.

4.4.2 Verification of the Size-Weight Illusion

To assess the SWI, a 100-point scale was used (heaviness scale [36]). After each trial, participants rated the felt physical strain with a number from 0 (no strain) till 100 (maximum strain).

4.4.3 Usability and Task-based Performance

Usability of a system is defined as the outcome measures efficiency, effectiveness, and user satisfaction [59]. According to [5], [60] the *time to task completion* (*TTC*) is a reliable and valid measure for efficiency for horizontal object-manipulation tasks. Hence, it was used to analyze the fast-precise bringing in order to investigate the effect of SWI and different *control strategies* on usability. Using the motion tracking data, the beginning is set via a velocity threshold (v_{start} > 0.02 m/s) and ended after the resulting velocity went under v_{end} = 0.01 m/s.

The *positioning path length* (*PPL*) was applied as a measure for efficiency of the slow-precise positioning task. The *PPL* is derived from the efficiency measures to find a way out of a labyrinth, like they are discussed in algorithmic geometry [61]. The shorter the *PPL*, the more efficient the positioning task. It is calculated from the point on when the acceleration of the manipulator becomes smaller than zero, which results in the following relation:

$$PPL = \sum_{i=t_{start}}^{t_{end}} \left|\vec{d}_{i+1} - \vec{d}_i\right| \tag{4}$$

$$t_{start} = t(a_i < 0); t_{end} = t(v_i = 0) + 2s;\ \vec{d}_i = \binom{x_i}{y_i}$$

Where a_i and v_i indicate the first acceleration, velocity value (after the initial push) that is smaller or equal to zero. Step size i is one frame (at 100Hz). The position vector d_i is defined by the position x_i and y_i of the system at the time $t = t_i$.

Degree of fulfillment (DF) was used as a measure for effectiveness of the positioning task. We defined DF as the absolute deviation of the end-position of the object p_{end} and the actual position after the assembly in the MayTec aluminum frame p_{target}:

$$DF = \left|\vec{p}_{target} - \vec{p}_{end}\right| \tag{6}$$

The vector $\vec{p}$ consists of the x- and y-component at the time t = t_{end} and t_{target}, which is after mounting the object into the MayTec aluminum frame.

The aforementioned 100-point strain scale was also used to measure subjective load in terms of user satisfaction. Hence, we assumed if the reported strain is lower, users are more satisfied with the system.

To analyze the different control strategies, the observed dependent variables (*TTC*, *PPL*, *DF*, and 100-point scale) were averaged over a *control strategy* sequence, without the first reference trial (50-medium). In that way, each *control strategy* was based on the same prior condition. An exemplary mean for *TTC* and *compensatory* would be the average of 100-large, 0-small, and 100-large, where n denotes the numbers of trials within one control strategy:

$$TTC_{compens} = \frac{\sum(TTC_{100-L} + TTC_{0-S} + TTC_{100-L})}{n-1} \tag{7}$$

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TOH.2017.2757925, IEEE Transactions on Haptics

5 Results

5.1 Statistical Analysis

We conducted a repeated measure 2 (*size*) x 3 (*weight*) x 2 (*movement type*) ANOVA. To analyze the influence of the above-mentioned different assistance strategies, the factor *control strategies* was investigated using a one-way ANOVA. The achieved results in *TTC*, *PPL*, and *100-point scale* were averaged over the course of each assistance strategy. In case the assumption of sphericity was violated (Mauchly's test, $p < 0.05$), the Greenhouse-Geisser correction was applied. Homogeneity was tested using Levene's test for equality of variances. The normality assumption was checked graphically using histograms and Q-Q plots as well as by applying the Shapiro-Wilk test. In addition to classical frequentist statistics, the Bayes Factor BF_{10} and Cauchy prior width $r = 0.707$ [62] was used to quantify the evidence for the alternative hypothesis relative to the null hypothesis [63]. The significance level was set to $\alpha = 0.05$. We used the classification of [62] for the Bayes Factor (BF): $1 < BF < 3$ (anecdotal evidence), $3 < BF < 10$ (moderate evidence), and $BF > 10$ (strong evidence). Effect sizes are classified using Cohen's benchmark: small (η^2, $\omega^2 = 0.01$), medium (η^2, $\omega^2 = 0.06$), and large (η^2, $\omega^2 = 0.14$) [64], [65]. MATLAB and MS EXCEL were used for data preparation; JASP and R were used for statistical analysis.

5.2 Indices for Sensorimotor Prediction and Size-Weight Illusion

Table 1 summarizes the descriptive results for *load force fast-imprecise* and *slow-precise* as well as for the *100-point scale*, *TTC*, *PPL*, and *DF*. Please consider that especially the force values cannot be taken as a design basis. They only serve as objective measures to infer to influences of object size, weight, and movement type on human motor control. Fig. 4 depicts the results itemized by object *size*, *weight*, and *movement type*.

5.2.1 Peak Load Force

Analyzing peak load force reveals no main effect of *size*, $F(1,38) = 0.37$, $p = 0.548$, $\eta_p^2 = 0.01$, $\omega^2 < 0.001$, $BF_{10} = 0.11$. This basically originates from the strong main effect *movement type*, $F(1,38) = 68.93$, $p < 0.001$, $\eta_p^2 = 0.64$, $\omega^2 = 0.62$, $BF_{10} = 7.7e+67$ and interaction effect of *size*movement type*, $F(1,38) = 18.71$, $p < 0.001$, $\eta_p^2 = 0.32$, $\omega^2 = 0.30$, $BF_{10} = 2.58e+67$. This fact can be seen in Fig. 4 where larger objects are pushed with higher peak load forces in fast movements, but with less force in precise movements. The remaining main effect *weight* did not show significant influences, $F(2,78) = 1.81$, $p = 0.171$, $\eta_p^2 = 0.04$, $\omega^2 = 0.02$, $BF_{10} = 0.04$ so do the interactions of *weight*movement type*, $F(2,78) = 1.31$, $p = 0.275$, $\eta_p^2 = 0.03$, $\omega^2 = 0.01$, $BF_{10} = 3.9e+64$ and *size*weight*movement type*, $F(2,78) = 0.45$, $p = 0.637$, $\eta_p^2 = 0.01$, $\omega^2 < 0.001$, $BF_{10} = 5.00e+62$. To get a better understanding of the mechanisms within each *movement type* post-hoc analyses using repeated 2 (*size*) x 3 (*weight*) ANOVAs have been applied (Table 2).

Peak Load Force – Fast-Imprecise: *Size* had a significant main effect on peak load force in the fast-imprecise movement. This translates in the finding that the participants invested higher forces on larger objects compared to smaller objects (Fig. 4, average increase of $M = 7.9\%$, $SD = 2.7\%$).

TABLE 1
DESCRIPTIVE DATA ACCORDING THE BETWEEN-FACTOR TYPE AND WITHIN-FACTORS SIZE AND WEIGHT

		$F_{1stpeak}$ [N/s] fast			$F_{1stpeak}$ [N/s] precise			100-point scale fast			100-point scale precise			*TTC* [s]			*PPL* [mm]			*DF* [mm]		
size	*weight*	*M*	*SD*	N	*M*	*SD*	N	*M*	*SD*	N	*M*	*SD*	N	*M*	*SD*	N	*M*	*SD*	N	*M*	*SD*	N
small	0	199.33	118.00	40	86.41	38.88	40	58.24	16.24	21	44.67	25.63	21	6.49	1.06	40	687.5	277.0	39	16.1	13.2	38
	50	206.60	89.65	40	88.43	48.12	40	64.00	15.74	21	42.95	25.64	21	6.58	1.23	40	653.3	247.2	39	12.9	14.0	38
	100	214.41	99.84	40	93.19	48.72	40	69.43	14.89	21	48.62	24.70	21	6.68	1.06	40	676.4	269.3	39	13.5	12.7	38
large	0	212.66	93.70	40	77.43	44.69	40	52.10	20.86	21	38.29	25.45	21	6.36	1.06	40	718.0	290.1	39	17.0	16.4	38
	50	227.61	94.19	40	73.10	40.94	40	51.52	17.89	21	41.57	22.32	21	6.65	1.00	40	723.3	266.3	39	16.5	15.8	38
	100	234.53	87.68	40	78.14	38.59	40	59.19	17.40	21	50.38	25.39	21	7.18	1.76	40	725.8	302.0	39	16.3	13.9	38

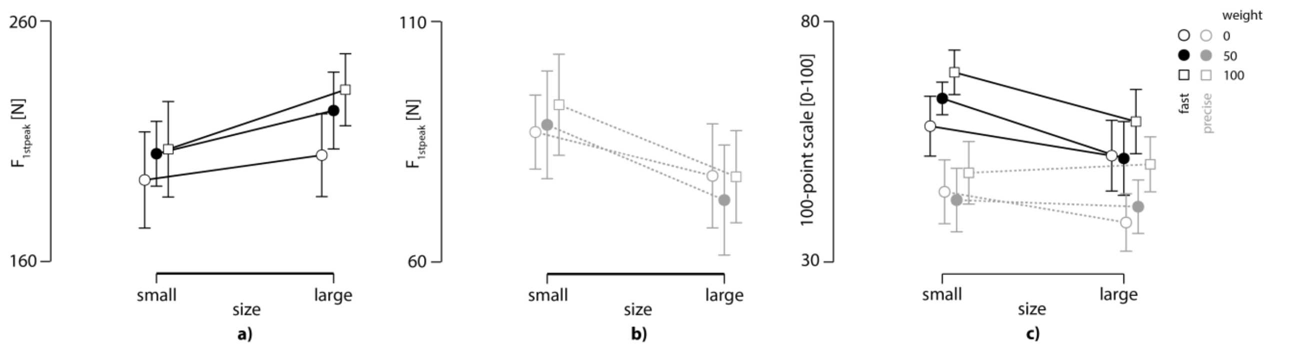

Fig. 4. Load force at the initial first peak for the three *weight* and two object *sizes* for **a)** fast-imprecise and **b)** slow-precise movement. **c)** Subjective rating of perceived strain after experiencing each *size* x *weight* condition on a 100-point scale, where 0 indicates no strain and 100 maximum strain. Solid black indicates fast-imprecise, dashed grey indicates slow-precise. Error bars indicate the 95% confidence interval.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TOH.2017.2757925, IEEE Transactions on Haptics

TABLE 2
STATISTICS FOR THE APPLIED ANOVAS – *PEAK LOAD FORCE*

	F	*df*	*p*	η_p^2	ω^2	BF_{10}
	$F_{1stpeak\_fast}$ [N/s]					
size	8.17	1,39	0.007	0.17	0.15	3.23
weight	2.00	2,78	0.143	0.05	0.02	0.34
*size*weight*	0.13	1.74,67.94	0.847	0.01	< 0.001	0.10
	$F_{1stpeak\_precise}$ [N/s]					
size	8.44	1,39	0.006	0.18	0.15	18.88
weight	0.45	1.60,62.45	0.446	0.01	< 0.001	0.07
*size*weight*	0.38	2,78	0.687	0.01	< 0.001	1.48

TABLE 3
STATISTICS FOR THE APPLIED ANOVAS – *100-POINT SCALE*

	F	*df*	*p*	η_p^2	ω^2	BF_{10}
	100-point scale_fast [0-100]					
size	21.60	1,37	< 0.001	0.37	0.35	3.73e+4
weight	6.34	2,74	0.003	0.15	0.12	11.85
*size*weight*	1.30	2,74	0.279	0.03	0.01	1.7e+5
	100-point scale_precise [0-100]					
size	1.56	1,20	0.226	0.07	0.03	0.30
weight	6.27	1.51,30.18	0.009	0.24	0.20	38.06
*size*weight*	1.99	2,40	0.150	0.09	0.04	12.12

Peak Load Force – Slow-Precise: Size had a significant main effect on peak load force in the slow-precise movement, but in a different direction. The surprising fact that the sensorimotor prediction according to the size cue is inverted in the slow-precise movement is (which can be seen in Fig. 4). Small objects are manipulated with higher peak forces (average increase of $M = 17.3$ %, SD = 4.1 %) compared to larger ones.

5.2.2 Subjective Strain with the 100-Point Scale

Analyzing the subjective answers regarding the *100-point strain scale* reveals significant results for *size*, $F(1,20) = 17.12$, $p < 0.001$, $\eta_p^2 = 0.46$, $\omega^2 = 0.42$, $BF_{10} = 6.46$, *weight* $F(2,40) = 9.63$, $p < 0.001$, $\eta_p^2 = 0.33$, $\omega^2 = 0.29$, $BF_{10} = 18.60$ and *movement type* $F(1,20) = 13.76$, $p = 0.001$, $\eta_p^2 = 0.41$, $\omega^2 = 0.37$, $BF_{10} = 1.6e{+}11$. Significant interaction effects for *size*movement type*, $F(1,20) = 35.57$, $p < 0.001$, $\eta_p^2 = 0.64$, $\omega^2 = 0.61$ and *size*weight*movement type*, $F(2,40) = 6.68$, $p = 0.003$, $\eta_p^2 = 0.25$, $\omega^2 = 0.21$ are present in the data. No significant interaction of *size*weight* indicates a robust subjective difference originating from *size* cues and *weight* independently from their combination, $F(2,40) = 0.30$, $p = 0.741$, $\eta_p^2 = 0.02$, $\omega^2 < 0.001$. It has to be taken into account that again *movement type* highly influences the subjective impression of physical strain. Again the interaction of *size*movement type* reveals different influences of object *size* cues for fast-imprecise and slow-precise movements (Table 3).

100-Point Scale – Fast-Imprecise: Size and *weight* had significant main effects on subjective strain in the fast-imprecise movement. No interaction effect of *size*weight* displays that independently from mass the illusory size effect persists.

100-Point Scale – Slow-Precise: *Size* did not reveal significant effects on subjective experience in the slow-precise positioning task. *Weight* significantly influenced the answers on the 100-point scale though. Likewise, the interaction of *size*weight* had no significant effect.

Concluding, load force analysis displays higher forces for larger objects in fast-imprecise and for smaller objects in slow-precise manipulations. According the 100-point scale SWI is present in the fast-imprecise movement and diminishes in the slow-precise positioning (*H1*).

5.3 Size Cues Influence Task Performance of Precise, but not of Imprecise Manipulations

The second part of the analysis sheds some light on the influence of visual object size cues on efficiency (*TTC* and *PPL*) and effectiveness (*DF*) of bimanual horizontal manipulations. Fig. 5 depicts the results itemized by object *size, weight*, and *movement type*. Table 4 summarizes the statistical results.

Time to Task Completion – Fast-Imprecise: Although *size* cues induced larger initial interaction forces no significant main effect of *size* on *TTC* is present in the data, but as expected, *weight* had a significant influence on efficiency. No significant interaction of *size*weight* was present.

Positioning Path Length – Slow-Precise: *Size* had a significant main effect on *PPL* in the precise positioning task. Whereas *weight* and the interaction of *size*weight* had no significant influence on *DF*.

Degree of Fulfillment – Slow-Precise: *Size* had a significant main effect on *DF* in the precise positioning task. Again *weight* and the interaction of *size*weight* had no significant influence on *DF*.

5.4 Control Strategy has no Significant Influence on Usability

Finally, the influence of the three control strategies (*static*, *compensatory*, and *mismatch*; see 3.1 and Fig. 3) on efficien-

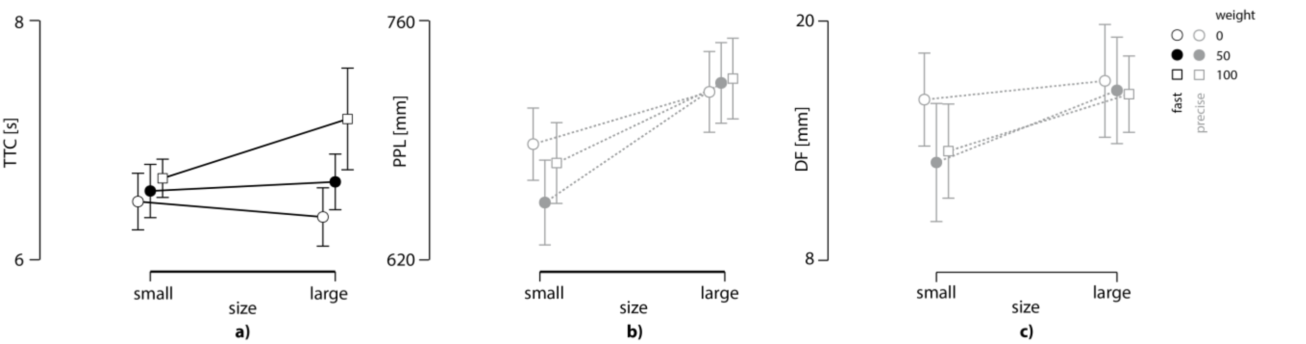

Fig. 5. **a)** *TTC*, **b)** *PPL*, and **c)** *DF* for the three weight and two object sizes. *TTC* is only considered for the fast-imprecise movement, *PPL* and *DF* only for the slow-precise movement. Error bars indicate the 95% confidence interval.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TOH.2017.2757925, IEEE Transactions on Haptics

TABLE 4
STATISTICS FOR THE APPLIED ANOVAS – *TTC*, *PPL*, *DF*

	TTC [s]					
	F	*df*	*p*	η_p^2	ω^2	BF_{10}
size	1.31	1,39	0.139	0.06	0.03	0.33
weight	7.47	2,78	0.001	0.16	0.14	30.58
*size*weight*	2.74	2,78	0.071	0.07	0.04	8.47
	PPL [mm]					
	F	*df*	*p*	η_p^2	ω^2	BF_{10}
size	30.95	1,38	< 0.001	0.45	0.43	3.4e+4
weight	0.92	2,76	0.405	0.02	< 0.001	0.09
*size*weight*	0.64	1.73,64.11	0.510	0.02	< 0.001	903.35
	DF [mm]					
	F	*df*	*p*	η_p^2	ω^2	BF_{10}
size	4.76	1,37	0.036	0.11	0.09	5.70
weight	1.36	2,72	0.263	0.04	0.01	0.14
*size*weight*	0.64	1.73,64.11	0.510	0.02	< 0.001	0.04

TABLE 5
STATISTICS FOR THE APPLIED ANOVAS – *CONTROL STRATEGIES*

	TTC [s]					
	F	*df*	*p*	η_p^2	ω^2	BF_{10}
ctrl. strategy	1.20	2,40	0.311	0.06	0.01	0.11
	PPL [mm]					
	F	*df*	*p*	η_p^2	ω^2	BF_{10}
ctrl. strategy	1.00	1.61,60.98	0.359	0.03	< 0.001	0.18
	DF [mm]					
	F	*df*	*p*	η_p^2	ω^2	BF_{10}
ctrl. strategy	0.96	1.01,38.19	0.333	0.03	< 0.001	0.19
	100-point scale [0-100]					
	F	*df*	*p*	η_p^2	ω^2	BF_{10}
ctrl. strategy	1.20	2,40	0.311	0.06	0.01	0.11
move type	14.82	1,20	< 0.001	0.42	0.39	1.6e+9
*ctrl*move*	2.89	1.49,29.71	0.085	0.13	0.08	3.2e+7

cy (*TTC* and *PPL*), effectiveness (*DF*) and subjective experience (*100-point scale*) of bimanual horizontal manipulations was analyzed. Fig. 6 shows the interaction plots for each *control strategy* and measurement. Table 5 summarizes the statistical results.

The within-factor *control strategy* has no significant effect on *TTC*, *PPL*, and *DF*. The *100-point scale* also did not show significant main effects of *control strategy*, but of *movement type* (see also 5.2.2). The interaction of *control strategy*movement type* was not significant. Globally, the control strategy based on different target inertias m_t, does not have statistical influence on task performance and subjective strain in our data set (*H3*).

5.5 Qualitative Findings

Besides quantitative data, the participants were asked questions about their perception of different experimental conditions and individual preferences for a potential control strategy. We asked the participants to judge how many different weights were used to simulate different admittance conditions, which 75 % correctly answered with the number "three". Only one participant was not able to perceive different inertial mass conditions. The question, if they want an object related robot control behavior, resulted in a symmetrical 50/50 distribution. Half of the participants wanted the same feedback for each object size (*static*), the other half wanted larger objects to be displayed as heavier than smaller objects (*compensatory*). No one reported to prefer the control condition (*mismatch*).

6 DISCUSSION

6.1 Expectation-Based SWI Occurs in Imprecise-fast Bimanual Manipulations, and Diminishes in Precise-Slow Positioning

The large object was manipulated with significant higher initial force in the fast-imprecise manipulation and each weight condition. This supports the statement that larger objects induce higher interaction forces [15]. In contrast to [15], this time the participants simultaneously and consistently judged the smaller object to be heavier in this condition. Hence, SWI was present and referring to the effect sizes can be accepted as strong and consistent in bimanual horizontal fast-imprecise manipulation tasks (*H1*). This can be an indicator for the expectation-based theory of haptic illusions [41] and strongly encourage the idea to implement object size related adaption in variable admittance controls. This effect will increase, if it is possible to manipulate the object directly without using handles and haptic perception of object size is involved (e.g. exoskeletons, hands-on control in IADs) [42]. SWI related issues have to be taken into account in the design and implementation of novel power-assisting devices, not least because of usability and stability issues [27].

In the slow-precise positioning a reversed sensorimotor prediction (small object induces higher initial force peak) and diminishing SWI (no subjective difference between small and large object) was found in this data set. Our opinion is, backed by open comments of the participants, that in the precise-slow positioning (with objectively significant lower forces), inertia and object size do not

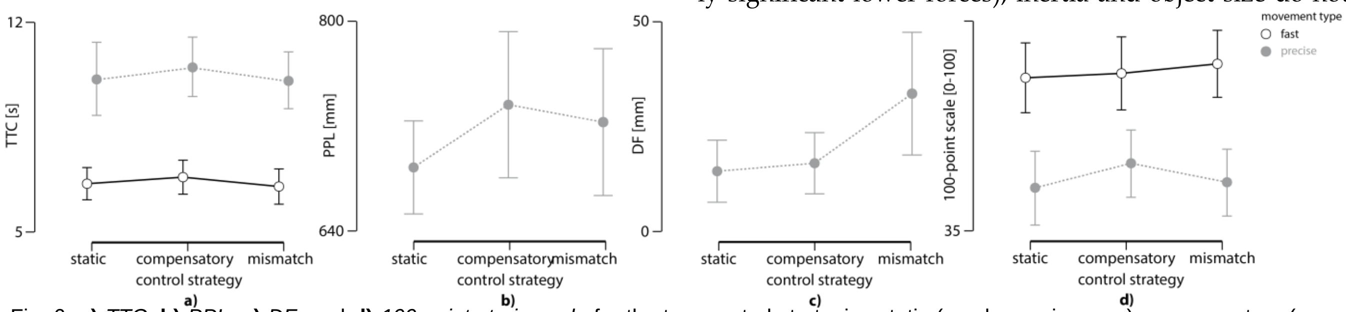

Fig. 6. **a)** *TTC*, **b)** *PPL*, **c)** *DF*, and **d)** *100-point strain scale* for the tree control strategies static (no change in mass), compensatory (compensating SWI), and mismatch (control group, amplifying SWI). Error bars indicate the 95% confidence interval.

play such a big role to the participants' perception. Most participants replied that they were concentrating on fitting the object in the positioning-frame. In doing so, according to the comments, it felt easier with a smaller object and therefore one was more confident and therefore manipulated with higher forces.

6.2 Influence of Object Size on Task Performance in Precise Positioning

No influence of object size on efficiency of the fast-imprecise task was measurable, which is similar to the findings of [49, 50]. In the presented task, it was indeed possible to be faster, but the high effect of object size at the initial start did not result in higher efficiency of the whole imprecise-fast task.

Additionally, this fact again changes for the precise-slow positioning. Both, efficiency (*PPL*) and effectiveness (*DF*) were heavily influenced by object size cues (*H2*). The trivial result that larger objects are harder to position supports the above mentioned outcome that smaller objects are manipulated more confidently in slow-precise positioning tasks. Hence, special diligence should be taken in use cases with large and bulky objects.

6.3 Stability vs. Task-Based Performance

Classical passivity-based approaches use higher admittance parameters to improve stability of compliance control of robotic manipulators. But, the admittance parameters virtual mass m_t [5], [51] and damping c_t [22], [29], [66] (2) highly influence manipulation performance. This is also present in the data set at hand, with a high influence of m_t on *TTC* in the fast-imprecise bringing. There are no such effects based on m_t found in the slow-precise task (no effect on *PPL* or *DF*). Mass m_t not only influences objective task performance, but also subjective experience in the fast-imprecise task and surprisingly, also in the slow-precise task, where only low accelerations take place. Therefore [23], [29], [30] recommend to use lower values for fast-imprecise and higher values for slow-precise movements, which again contradicts the initial stability issue, as well as the subjective experiences of the participants. If the human applies high forces (e.g. due to object size cues of a large object) or changes in acceleration in fast-imprecise movements with low admittance parameters, instability is likely to occur. In addition, passivity based approaches with high admittance parameters may guarantee stability, but also require higher operator effort for the compliant movement [27], which in our opinion can lead to lower usability and acceptance of the system. The most common technique to ensure stability is increasing target damping c_t while the target inertia m_t remains constant [21], [67]. This is effective, but c_t has much worse influence on operator effort than m_t [22], [27], [29], [66]. Hence, we suggest to apply the initial proposed solution of [27], to increase m_t instead of c_t, with less operator effort. Especially, in fast-imprecise movements where fast and high changes of force and acceleration can occur, higher m_t according to object size could guarantee higher stability without any effect on the subjective experience of the user.

We did not find significant effects of control strategy on task performance, as well as no strict subjective preferences for any strategy (50% static, 50% compensatory, *H3*). This leads us to the assumption that an individual adaption could be necessary, to meet each operator's expectations. In addition, the control strategies were averaged over respectively only few trials and therefore lack of reliability. Since, there will be an adaptation of force inputs to the different object size and mass combinations [68] a control strategy will have to have an adaptive behavior. Since [27] proposed an online recursive stability index that enables operation in the stable region, an online adaptation on the basis of m_t will be possible. Still, it has to be considered that SWI will persist and the subjective experience of the participants that smaller objects feel awkwardly heavier than larger ones, will stay.

6.4 Future Work and Relevance to Robotics

This study demonstrated the effect of erroneous interaction force applied by the user, because of different object sizes, which results in deficient perceived heaviness. As Groten et al. [69] stated, communication between two humans takes place via the haptic channel in form of an intention integration. We assume this integration has to happen in the robot control as well and therefore encourage the idea of implementing an adapted version of the Bayesian framework of [15]. Based on the concepts of error-based learning and the expectation-based theory of haptic illusions this novel variable admittance concepts should include prior knowledge of object characteristics into the robot control strategy. Although the control strategies *static*, *compensatory*, and *mismatch* did not show significant differences, it has to be taken into account that SWI had a very high effect on initial interaction force and therefore can lead to instability. Hence, it is crucial to model human expectation, which without doubt is a huge *challenge*, but also a tremendously important *chance* to overcome the *nuisance* of weight illusions. The knowledge of human expectation and intention integration will make this possible, but probably will also require customizable devices to meet the individual user's perception and prior knowledge. We encourage designers of novel power-assisting devices to implement feedback about the admittance parameters m_t and c_t. In that way, not only the machine can learn about the human's intention, but the human can visually perceive and learn different adjustments and connect these to his/her proprioceptive perception.

6.5 Recommendations

We propose an assistance framework that implements object size cues in the configuration of novel variable admittance controls. A reference level (RL) should define each individual's accepted assistance level (or admittance configuration m_t and c_t). This can be achieved in a so called "method of adjustment", where the operator frequently adapts m_t and c_t to his/her own preferences or needs. After a certain number of trials these adaptions are averaged and adapted accordingly. This RL has to stay under a pre-defined ergonomic upper limit, e.g. DIN EN 1005-3 (~230 N push, ~160 N pull), and can vary accordingly to external influences like the environment (hectic/slow, work/leisure), gender, age, and similar. Based on this RL either an a priori fixed (*static*) strategy, where unaware of object size one and the same assistance is applied, or an object size related (*compensatory*) strategy can be implemented. If the latter one is selected, knowledge about the human perception of inertial mass difference will be needed, which the authors will provide in future work.

ACKNOWLEDGMENT

This research has been funded by the German Federal Ministry of Education and Research (BMBF, project KobotAERGO). The authors wish to thank Michael Mühlbauer, Sebastian Harslem, and Moritz v. Freymann for their assistance in conducting the experiments and Moritz Körber, Daniel Meyer, and Jakob Reinhardt for their comments on the manuscript.

REFERENCES

[1] T. B. Sheridan, "Human–Robot Interaction," *Hum. Factors*, vol. 58, no. 4, pp. 525–532, Jun. 2016.

[2] W. Wannasuphoprasit, P. Akella, M. Peshkin, and J. E. Colgate, "Cobots: a Novel Material Handling Technology," *Proc. IMECE, ASME*, pp. 171–178, 1998.

[3] M. Peshkin and J. E. Colgate, "Cobots," *Ind. Robot An Int. J.*, vol. 26, no. 5, pp. 335–341, Jul. 1999.

[4] D. a. Abbink, M. Mulder, and E. R. Boer, "Haptic shared control: smoothly shifting control authority?," *Cogn. Technol. Work*, vol. 14, no. 1, pp. 19–28, Mar. 2012.

[5] J. Schmidtler, M. Korber, and K. Bengler, "A trouble shared is a trouble halved — Usability measures for Human-Robot Collaboration," in *2016 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, 2016, pp. 000217–000222.

[6] E. Frieling, M. Buch, and J. Wieselhuber, "Alter(n)sgerechte Arbeitssystemgestaltung in der Automobilindustrie - die demografische Herausforderung bewältigen," *Z. Arbeitswiss.*, vol. 60, no. 4, pp. 213–219, 2006.

[7] J. H. Verbeek, K. P. Martimo, P. P. F. M. Kuijer, J. Karppinen, E. Viikari-Juntura, and E. P. Takala, "Proper manual handling techniques to prevent low back pain, a Cochrane Systematic Review," *Work*, vol. 41, no. SUPPL.1, pp. 2299–2301, 2012.

[8] F. S. Fogliatto, G. J. C. Da Silveira, and D. Borenstein, "The mass customization decade: An updated review of the literature," *Int. J. Prod. Econ.*, vol. 138, no. 1, pp. 14–25, 2012.

[9] J. Schmidtler, V. Knott, C. Hölzel, and K. Bengler, "Human Centered Assistance Applications for the working environment of the future," *Occup. Ergon.*, vol. 12, no. 3, pp. 83–95, Sep. 2015.

[10] DIN EN ISO 10218-1, *DIN EN ISO 10218-1 - Robots and robotic devices - Safety requirements for industrial robots - Part 1: Robots*. 2012.

[11] ISO TS 15066, *ISO TS 15066 - Robots and robotic devices - Collaborative robots*. 2016.

[12] I. International Federation of Robotics, "World record: 248,000 industrial robots revolutionising the global economy," 2016.

[13] J. Krüger, T. K. Lien, and A. Verl, "Cooperation of human and machines in assembly lines," *CIRP Ann. - Manuf. Technol.*, vol. 58, no. 2, pp. 628–646, 2009.

[14] D. J. Murray, R. R. Ellis, C. a Bandomir, and H. E. Ross, "Charpentier (1891) on the size-weight illusion.," *Percept. Psychophys.*, vol. 61, no. 8, pp. 1681–1685, 1999.

[15] J. Schmidtler and K. Bengler, "Size-weight illusion in human-robot collaboration," in *2016 25th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*, 2016, pp. 874–879.

[16] A. Karniel, A. Peer, O. Donchin, F. a. Mussa-Ivaldi, and G. E. Loeb, "Haptic Human-Robot Interaction," *IEEE Trans. Haptics*, vol. 5, no. 3, pp. 193–195, 2012.

[17] A. De Santis, B. Siciliano, A. De Luca, and A. Bicchi, "An atlas of physical human–robot interaction," *Mech. Mach. Theory*, vol. 43, no. 3, pp. 253–270, Mar. 2008.

[18] O. Khatib, K. Yokoi, O. Brock, K. Chang, and A. Casal, "Robots in Human Environments: Basic Autonomous Capabilities," *Int. J. Rob. Res.*, vol. 18, no. 7, pp. 684–696, Jul. 1999.

[19] A. Cherubini, R. Passama, A. Crosnier, A. Lasnier, and P. Fraisse, "Collaborative manufacturing with physical human-robot interaction," *Robot. Comput. Integr. Manuf.*, vol. 40, no. August, pp. 1–13, 2016.

[20] C. Burghart, S. Yigit, and O. Kerpa, "Concept for human robot co-operation integrating artificial haptic perception," *Intell. Auton. Syst.*, vol. 7, pp. 38–45, 2002.

[21] V. Duchaine, B. Mayer St-Onge, D. Gao, and C. Gosselin, "Stable and intuitive control of an intelligent assist device," *IEEE Trans. Haptics*, vol. 5, no. 2, pp. 148–159, 2012.

[22] A. Lecours, B. Mayer-St-Onge, and C. Gosselin, "Variable admittance control of a four-degree-of-freedom intelligent assist device," in *2012 IEEE International Conference on Robotics and Automation*, 2012, no. 2, pp. 3903–3908.

[23] S. M. M. Rahman, R. Ikeura, S. Hayakawa, and H. Yu, "Manipulating objects with a power assist robot in linear vertical and harmonic motion: psychophysical-biomechanical approach to analyzing human characteristics to improve the control," *J. Biomech. Sci. Eng.*, vol. 6, no. 5, pp. 399–414, 2011.

[24] H. Kazerooni, "A Review of the Exoskeleton and Human Augmentation Technology," in *ASME 2008 Dynamic Systems and Control Conference, Parts A and B*, 2008, pp. 1539–1547.

[25] K. Kosuge and N. Kazamura, "Control of a robot handling an object in cooperation with a human," *Proc. 6th IEEE Int. Work. Robot Hum. Commun. RO-MAN'97 SENDAI*, pp. 142–147, 1997.

[26] J. E. Colgate, M. Peshkin, and S. H. Klostermeyer, "Intelligent assist devices in industrial applications: a review," *Proc. IEEE/RSJ Int. Conf. Intell. Robot. Syst.*, 2003.

[27] F. Dimeas and N. Aspragathos, "Online Stability in Human-Robot Cooperation with Admittance Control," *IEEE Trans. Haptics*, vol. 9, no. 2, pp. 267–278, Apr. 2016.

[28] R. Ikeura, H. Monden, and H. Inooka, "Cooperative motion control of a robot and a human," in *Robot and Human Communication, 1994. RO-MAN '94 Nagoya, Proceedings., 3rd IEEE International Workshop on*, 1994.

[29] V. Duchaine and C. M. Gosselin, "General model of human-robot cooperation using a novel velocity based variable impedance control," *Proc. - Second Jt. EuroHaptics Conf. Symp. Haptic Interfaces Virtual Environ. Teleoperator Syst. World Haptics 2007*, pp. 445–451, 2007.

[30] D. Abbink, "Neuromuscular Analysis of Haptic Gas Pedal Feedback during Car Following," Delft University of Technology, 2006.

[31] S. J. Lederman and R. L. Klatzky, "Haptic perception: A tutorial," *Attention, Perception, Psychophys.*, vol. 71, no. 7, pp. 1439–1459, Oct. 2009.

[32] E. B. Goldstein, *Sensation and perception*, 9th ed. Wadsworth: CENGAGE Learning, 2014.

[33] H. B. Helbig and M. O. Ernst, "Haptic perception in interaction with other senses," in *Human Haptic Perception: Basics and Applications*, M. Grundwald, Ed. Birkhäuser Basel, 2008, pp. 235–249.

[34] E. Burdet, D. W. Franklin, and T. E. Milner, *Human robotics: neuromechanics and motor control*. MIT Press, 2013.

[35] R. C. Miall and D. M. Wolpert, "Forward Models for

Physiological Motor Control," *Neural Networks*, vol. 9, no. 8, pp. 1265–1279, Nov. 1996.

[36] G. Buckingham and A. MacDonald, "The weight of expectation: Implicit, rather than explicit, prior expectations drive the size–weight illusion," *Q. J. Exp. Psychol.*, vol. 69, no. 9, pp. 1831–1841, Sep. 2016.

[37] A. M. Gordon, H. Forssberg, R. S. Johansson, and G. Westling, "Visual size cues in the programming of manipulative forces during precision grip," *Exp. Brain Res.*, vol. 83, no. 3, pp. 477–482, Feb. 1991.

[38] L. A. Jones, "Perception of Force and Weight : Theory and Research," *Psychol. Bull.*, vol. 100, no. 1, pp. 29–42, 1986.

[39] S. J. Lederman and L. a. Jones, "Tactile and Haptic Illusions," *IEEE Trans. Haptics*, vol. 4, no. 4, pp. 273–294, 2011.

[40] S. Kawai, F. Henigman, C. L. MacKenzie, A. B. Kuang, and P. H. Faust, "A reexamination of the size-weight illusion induced by visual size cues," *Exp. Brain Res.*, vol. 179, no. 3, pp. 443–456, 2007.

[41] H. E. Ross, "When is a weight not illusory?," *Q. J. Exp. Psychol.*, vol. 21, no. 4, pp. 346–55, 1969.

[42] R. R. Ellis and S. J. Lederman, "The role of haptic versus visual volume cues in the size-weight illusion.," *Perception & psychophysics*, vol. 53, no. 3. pp. 315–324, 1993.

[43] J. C. Stevens and L. L. Rubin, "Psychophysical scales of apparent heaviness and the size-weight illusion," *Percept. Psychophys.*, vol. 8, no. 4, pp. 225–230, 1970.

[44] E. L. Amazeen, "The Effects of Volume on Perceived Heaviness by Dynamic Touch: With and Without Vision," *Ecol. Psychol.*, vol. 9, no. 4, pp. 245–263, 1997.

[45] D. V. Cross and L. Rotkin, "The relation between size and apparent heaviness," *Percept. Psychophys.*, vol. 18, no. 2, pp. 79–87, 1975.

[46] G. Buckingham, "Getting a grip on heaviness perception: A review of weight illusions and their probable causes," *Exp. Brain Res.*, vol. 232, no. 6, pp. 1623–1629, 2014.

[47] M. a. Plaisier and J. B. J. Smeets, "Mass is all that matters in the size-weight illusion," *PLoS One*, vol. 7, no. 8, pp. 1–6, 2012.

[48] G. Buckingham, C. M. Byrne, J. Paciocco, L. van Eimeren, and M. a Goodale, "Weightlifting exercise and the size–weight illusion," *Attention, Perception, Psychophys.*, vol. 76, no. 2, pp. 452–459, Feb. 2014.

[49] P. E. Luebbers, G. Buckingham, and M. S. Butler, "The National Football League-225 Bench Press Test and the Size–Weight Illusion," *Percept. Mot. Skills*, vol. 124, no. 3, pp. 634–648, Jun. 2017.

[50] S. M. M. Rahman and R. Ikeura, "Investigating the factors affecting human's weight perception in lifting objects with a power assist robot," in *2012 IEEE RO-MAN: The 21st IEEE International Symposium on Robot and Human Interactive Communication*, 2012, pp. 228–233.

[51] J. Schmidtler, C. Harbauer, and K. Bengler, "Investigation of Human Behaviour in Pushing and Pulling Tasks for Direct Manipulation of a Collaborative Robot," in *Proceedings of the Human Factors and Ergonomics Society Europe Chapter*, 2014.

[52] E. Burdet, G. Ganesh, C. Yang, and A. Albu-Schäffer, "Interaction force, impedance and trajectory adaptation: By humans, for robots," *Springer Tracts Adv. Robot.*, vol. 79, pp. 331–345, 2014.

[53] P. Marayong and A. M. Okamura, "Speed-Accuracy Characteristics of Human-Machine Cooperative Manipulation Using Virtual Fixtures With Variable Admittance," *Hum. Factors J. Hum. Factors Ergon. Soc.*, vol. 46, no. 3, pp. 518–532, 2004.

[54] F. Faul, E. Erdfelder, A.-G. Lang, and A. Buchner, "G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences," *Behav. Res. Methods*, vol. 39, no. 2, pp. 175–191, May 2007.

[55] D. E. Adamo, B. J. Martin, and S. H. Brown, "Age-related differences in upper limb proprioceptive acuity," *Percept. Mot. Skills*, vol. 104, no. 3c, pp. 1297–1309, Jun. 2007.

[56] A. Seidl, "SizeGERMANY – the new German Anthropometric Survey Conceptual Design, Implementation and Results," 2009.

[57] E. R. Tichauer, "Some aspects of stress on forearm and hand in industry," *J. Occup. Environ. Med.*, vol. 8, no. 2, pp. 63–71, 1966.

[58] G. Buckingham, E. E. Michelakakis, and G. Rajendran, "The Influence of Prior Knowledge on Perception and Action: Relationships to Autistic Traits," *J. Autism Dev. Disord.*, no. April, 2016.

[59] *DIN EN ISO 9241-11 - Ergonomics of human-system interaction - Part 11: Usability: Definitions and concepts*. Berlin, 2016.

[60] R. K. Groten, "Haptic Human-Robot Collaboration: How to Learn from Human Dyads," Technical University of Munich, 2011.

[61] R. Klein, "Bewegungsplanung bei unvollständiger Information," in *Algorithmische Geometrie*, Berlin/Heidelberg: Springer-Verlag, 2005, pp. 315–372.

[62] F. D. Schönbrodt, E.-J. Wagenmakers, M. Zehetleitner, and M. Perugini, "Sequential Hypothesis Testing With Bayes Factors: Efficiently Testing Mean Differences.," *Psychol. Methods*, 2015.

[63] M. Körber, J. Radlmayr, and K. Bengler, "Bayesian Highest Density Intervals of Take-Over Times for Highly Automated Driving in Different Traffic Densities," *Proc. Hum. Factors Ergon. Soc. Annu. Meet.*, vol. 60, no. 1, pp. 2009–2013, Sep. 2016.

[64] J. Cohen, *Statistical power analysis for the behavioral sciences*. Academic press, 1988.

[65] D. Lakens, "Calculating and reporting effect sizes to facilitate cumulative science: A practical primer for t-tests and ANOVAs," *Front. Psychol.*, vol. 4, no. NOV, pp. 1–12, 2013.

[66] R. Ikeura, H. Monden, and H. Inooka, "Cooperative motion control of a robot and a human," *Proc. 1994 3rd IEEE Int. Work. Robot Hum. Commun.*, pp. 2–3, 1994.

[67] V. Duchaine and C. M. Gosselin, "Investigation of human-robot interaction stability using Lyapunov theory," *Proc. - IEEE Int. Conf. Robot. Autom.*, pp. 2189–2194, 2008.

[68] J. R. Flanagan and M. a Beltzner, "Independence of perceptual and sensorimotor predictions in the size-weight illusion.," *Nat. Neurosci.*, vol. 3, no. 7, pp. 737–741, 2000.

[69] R. Groten, D. Feth, R. L. Klatzky, and A. Peer, "The role of haptic feedback for the integration of intentions in shared task execution," *IEEE Trans. Haptics*, vol. 6, no. 1, pp. 94–105, 2013.

Jonas Schmidtler received his diploma (M.Sc. equivalent) in mechanical engineering and management from the Technical University of Munich, Germany, in 2013. He is currently working as a research associate at the Chair of Ergonomics at the Technical University of Munich. He is part of the research group Cooperative Systems and Automation. His research interests include human factors, Human-Robot Interaction, haptics, and psychophysics. He is a graduate student member of IEEE and member of the IEEE Robotics and Automation Society.

Klaus Bengler received his diploma (M.Sc. equivalent) in psychology from the University of Regensburg, Germany, in 1991 and a Ph.D. degree in 1995 in cooperation with BMW at the Institute of Psychology. In 1997 he joined BMW, was leader of the BMW usability laboratory, and active in topics of software ergonomics and evaluation of human-machine interfaces. Since May 2009, he has been head of the Chair of Ergonomics, Technical University of Munich, Germany, where he is active in research areas such as automated driving, digital human modeling, human-robot interaction, driver assistance HMI, and human reliability.