# Grasping New Material Densities

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## Abstract

When picking up objects, we prefer stable grips with minimal torque by seeking grasp points that straddle the object's center of mass (CoM). For homogeneous objects, the CoM is at the geometric center (GC), computable from shape cues. However, everyday objects often include components of different materials and densities. In this case, the CoM depends on the object's geometry and the components' densities.

We asked how participants estimate the CoM of novel, two-part objects. Across 4 experiments, participants used a precision grip to lift cylindrical objects comprised of steel and PVC in varying proportions (steel 3 times denser than PVC). In all experiments, initial grasps were close to objects' GCs; neither every-day experience (metals are denser than PVC) nor pre-exposure to the stimulus materials in isolation moved first grasps away from the GC. Within a few trials, however, grasps shifted towards the CoM, reducing but not eliminating torque. Learning transferred across the stimulus set, i.e., observers learnt the materials' densities (or their ratio) rather than learning each object's CoM. In addition, there was a stable 'under-reaching' bias towards the grasping hand.

An 'inverted density' stimulus set (PVC 3 x denser than steel) induced similarly fast learning, confirming that prior knowledge of materials has little effect on grasp point selection. When stimulus sets were covertly switched during an experiment, the unexpected force feedback caused even faster grasp adaptation.

Torque minimisation is a strong driver of grasp point adaptation, but there is a surprising lack of transfer following pre-exposure to relevant materials.

Keywords: Grasping behaviour, visuomotor learning, composite objects, novel materials, density estimation.

**Plain language summary (max 1500 characters)**

Have you ever grabbed a jug of milk that you thought was full, but turned out to be empty? The container moved upwards faster than you expected. Or you picked up an object by one end, only to find that the other end was much heavier, and you struggled not to drop it. These events are quite rare, however. Usually, when we lift an object, we automatically grasp it in the correct way with the right amount of force to smoothly complete a task (e.g. adding milk to tea). We ask: how do we manage this for unknown objects? Specifically, how do we successfully grasp objects made of two parts, with one part much denser (steel) than the other (PVC)? To select the best position to grip the object, so that it doesn't tip, we need to use knowledge of these two materials: that steel is 3 x denser than PVC. Surprisingly, our participants did not use their previous experience of these materials, when they were asked to lift novel objects. Instead, they acted as though steel and PVC were equally dense (i.e., had the same weight per $cm^3$). However, after lifting one object, they quickly learnt to grasp other novel objects in a near-ideal manner, when those objects were also made of steel and PVC but had different shapes. Our participants were just as fast to learn how to interact with 'trick' objects in which PVC was denser than steel. When we encounter a new set of objects, we don't trust our eyes to tell us about the objects' materials; only feeling is believing.

## Introduction

Grasping objects is a complex task that we nonetheless efficiently execute hundreds of times a day with relative ease. Optimal grasping behaviour, i.e., where and how to grasp an object, is dictated by the characteristics of (i) the human body and hand (the plant), (ii) the object (the target), and (iii) the planned activity (the task). The human hand has 27 kinematic degrees of freedom (Lin et al., 2000), while the arm adds another 7 (Desmurget & Prablanc, 1997; Lemay & Crago, 1996). Relevant muscles must be activated, each within a specific range of forces that they are able to exert (Zajac, 1989). Object properties that affect grasping behaviour include size and weight (Gordon et al., 1991a, 1991b; Gordon et al., 1993), friction (Glowania et al., 2017; Johansson & Westling, 1984; Klein et al., 2021; Paulun et al., 2016; Wing & Lederman, 2009), shape (Nguyen, 1988), material properties such as density (Buckingham et al., 2009; Gordon et al., 1993) and thus the center of mass (Eastough & Edwards, 2007; Goodale et al., 1994; Lederman & Wing, 2003; Lukos et al., 2007). The purpose of the grasp (e.g., grasping a bottle to pour vs. to hand it to someone) also dictates the optimal grasp type and position (Ansuini et al., 2008; Friedman & Flash, 2007).

Broadly, investigations of grasping behaviour have focussed on (i) grasp trajectories and hand shaping (Harris & Wolpert, 1998; Hoff & Arbib, 1993; Rosenbaum et al., 1999; Smeets & Brenner, 1999; Uno et al., 1989), (ii) grasp point selection (i.e., the locations at which the finger(s) and thumb make contact with the object, (Crajé et al., 2011; Crajé et al., 2013; Klein et al., 2020; Kleinholdermann et al., 2013; Paulun et al., 2014), and/or (iii) the load and grip forces applied at those positions (Baugh et al., 2012; Cole, 2008; Delhaye et al., 2024; Gordon et al., 1993; Loh et al., 2010; Salimi et al., 2003; Salimi et al., 2000). All three of these interact, e.g., when grasp points are constrained, this will generally affect grasping forces.

Most of the above studies employed stimuli composed of a single material. However, everyday objects are often composed of different materials with different densities. This complicates the optimal selection of grasping positions when trying to minimize force/torque. Here we focus on *grasp point selection* and in particular how this is modulated by the mass distribution within objects comprised of *different density materials* such as polyvinyl chloride (PVC) and metal (see Fig. 1).

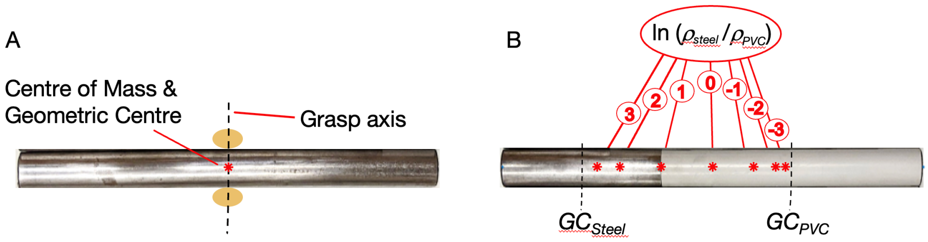


***Figure 1:*** *Centre of Mass (CoM) for a homogenous and a composite object.* ***(A)*** *homogenous (single material) object: the centre of mass and geometric centre (GC) are co-located and independent of density. A grasp axis through the CoM results in zero torque.* ***(B)*** *Composite (two-part) object: the centre of mass (red stars) depends on the log density ratio (LDR) of the metal and polyvinyl chloride (PVC) components. When the densities are equal ($\rho_{Steel}=\rho_{PVC}$; LDR=0) the CoM is equal to the GC. Increases or decreases in LDR move the CoM asymptotically towards the geometric centre of the heavier component at $GC_{Steel}$, or $GC_{PVC}$. Supplementary Information Section S1 gives equations for CoM, and Fig. S1A shows the relationship between LDR and CoM for all stimulus objects.*

Human grasp point selection can be understood using the logic of optimal control theory: a set of cost or penalty functions are minimized to estimate the optimal state (Diedrichsen et al., 2010; Shadmehr & Krakauer, 2008; Todorov, 2004; Todorov & Jordan, 2002). One of these costs is torque; an object will rotate under torque, unless sufficient (and costly) counteracting force is applied. This is particularly difficult under a pincer grip, when a single finger opposes the thumb, and torsional friction must be generated via increasing the grip force. When using a pincer grip, therefore, we prefer grasp points that are close to, or straddle the centre of mass (CoM) (Eastough & Edwards, 2007; Endo et al., 2011; Goodale et al., 1994; Lederman & Wing, 2003). For a purely vertical lift, however, grasp points can merely straddle a vertical axis through the CoM (e.g., holding a weight via a string). Torque does appear to be estimated before contact: subjects make anticipatory increases in the normal grip force in order to prevent rotation under torque (Wing & Lederman, 1998).

Whilst it is clear that torque minimisation is a factor in grasp point selection, little is known about how density information is inferred or learnt in order to select appropriate grasp locations around the CoM, particularly within composite objects. Many graspable objects are composed of different materials (e.g., tools such as hammers, knives, and axes). For such composite objects, the CoM depends on the relative densities of the components in addition to the object geometry (Fig. 1).

Here we focus on how we learn and apply information about material densities within two-part composite objects in order to minimise torque. Participants were required to lift and move cylindrical objects comprised of steel and PVC in varying proportions, using a precision grip. Specifically, we ask: (i) do visual density cues guide grasp points *before* any force feedback occurs (i.e., the mass and torque experienced on lifting), (ii) how do prior expectations of material densities combine with recent visual-haptic experience to determine grasp points, and (iii) does information about material densities generalise across objects composed of these materials with different 3D geometries?

This article is published as part of a special issue in the journal Multisensory Research honouring the life and work of Vincent Hayward, who passed away in May 2023. Vincent Hayward's work on haptic shape perception has significantly advanced our understanding of touch-based interactions with objects and inspired us to pursue the current line of research. Vincent was the first to point out the importance of tactile (force field) and proprioceptive (positional) interactions for haptic shape perception (Robles-De-La-Torre & Hayward, 2001). He also emphasized that both the pattern of local skin deformation and the change in local surface orientation are essential cues for haptic shape (Dostmohamed & Hayward, 2005; Wijntjes et al., 2009). Vincent highlighted the importance of considering mechanisms operating on different scales, to understand haptic shape perception, from microscopic texture cues to macroscopic surface orientation cues, focussing on haptic invariants and the use of prior knowledge for disambiguating haptic shape (Hayward, 2008; Moscatelli et al., 2016; Moscatelli et al., 2015; Ziat et al., 2010). He also showed that prior expectations of density differentially affect perception and action in the size-weight and size-inertia illusions (Platkiewicz & Hayward, 2014). Vincent also explored the role of different cues in haptic material perception such as friction, roughness, compliance and temperature (André et al., 2011; Wang & Hayward, 2010; Wiertlewski et al., 2011). This work led us (WJA and MOE) to write a grant proposal together with Vincent back in 2016, which was the starting point for the current work.

To preview the key findings of the current paper: participants initially grasp all objects close to their geometric centre (GC), but then quickly (within a few lifts) adjust their grasp positions for bipartite objects towards their centre of mass. In other words, they quickly learn density information and apply it to the full stimulus set, rather than learning the CoM for individual objects (Expt. 1). In Experiments 2 and 3 we show that when material densities change unexpectedly, observers are similarly fast (in fact even faster) to learn the new density relationship (Expt. 2). This fast adaptation to new object properties occurs whether the two materials' relative densities are in line with prior assumptions (steel denser than PVC) or reversed (PVC heavier than steel: Expts. 2 & 3). Surprisingly, prior experience with the object's two separate components does little to guide initial grasping locations of composite objects. Our data suggest that torque minimisation is a strong predictor of grasp point selection, even when no explicit instruction is given to prevent object rotation. However, we also find two stable biases: asymptotic grasp locations remain biased towards the geometric centre (Expts. 1-4), and there is a bias for under-reaching, i.e. for grasp locations to be biased toward the initial position of the grasping hand (Expts. 1-4).

## General Methods: Stimuli

To manipulate the mass distribution of compound objects we created two (visually identical) sets of stimuli, each consisting of nine, 32cm long hollow cylinders (diameter 2cm). They were made of steel and/or PVC in proportions linearly ranging from 0 to 1, including a PVC only and a steel only object. In the first set, which followed a natural density ratio, the steel portion was 3 times denser than the PVC (total stimulus mass: 68g - 204g). In the second set, this relationship was reversed: the density of PVC was 3 times denser than the steel side. This was achieved by inserting a slightly shorter metal cylinder inside the PVC section (total stimulus mass: 164g - 492g). The friction and compliance of the materials were similar (a sample of colleagues could not distinguish the two materials from touch alone, when mass information was unavailable, and objects were at skin temperature). Given the salient visual differences between the materials, however, any difference in the tactile properties, following object contact, was redundant.

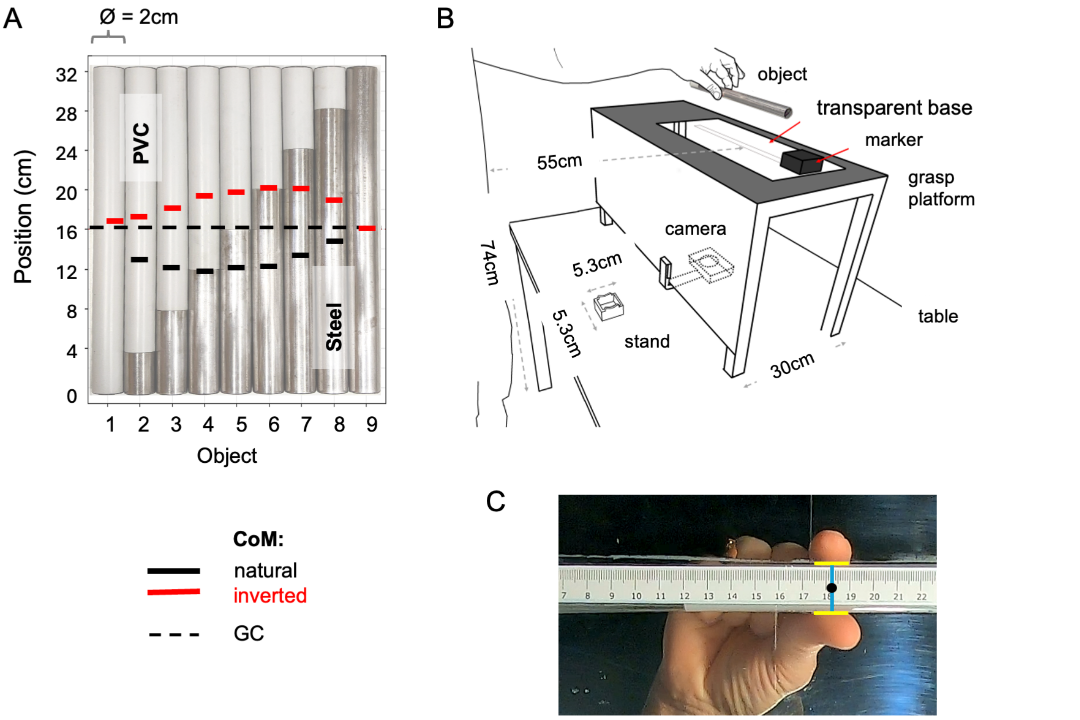


***Figure 2:*** *Stimuli and experimental set-up.* ***(A)*** *Stimulus objects: horizontal black markers show the CoM for the Natural Density set; red markers show the CoM for the Inverted Density set; black horizontal dotted line shows the GCs.* ***(B)*** *Experimental setup: the participant stood in front of the grasp platform. Before each trial, the experimenter placed the object on the transparent base with its right side touching the marker. The participant used their dominant hand to lift the object with a precision pincer grip and place it on the stand.* ***(C)*** *The grasp position was determined by identifying the axis (blue) connecting the mid-points of the two contact areas (yellow). The grasp point is the centre of this axis.*

## General Methods: Setup & Procedure

Participants stood facing a small platform within comfortable reaching distance (Fig. 2B). The platform had a transparent top onto which the stimuli were placed and a camera (Apeman A77 Action Camera) under this platform recorded finger positions. Although the participants were not aware of the camera's position, they were informed that their hand movements would be recorded. After lifting, participants placed the stimulus on a small stand in front of the platform. If the object's center of mass was not within the width of the stand, the objects would tip over once placed, and this happened frequently during initial trials. Consequently, participants were implicitly encouraged to grasp at, or at least estimate, each object's center of mass. Each trial consisted of a lift followed by the object's placement on the stand.

Participants were instructed to grasp the object with two fingers using a precision pincer grip, to lift it in one single fluid motion, before placing it on the stand. Neither the centre of mass, nor where to place the fingers on the object were mentioned. Before starting the experimental trials, 5 practice trials were completed with dummy objects (cylindrical shapes, made from a homogeneous PVC material, different from the PVC in the main experiment) so that the participants became familiar with the task.

Each trial began by the experimenter placing a stimulus object in the center of the grasp platform, 55 cm in front of the participant (see Fig. 2B). This was done using two hands so that the participant could not gain any density / CoM information by watching the experimenter. Trial order was independently randomised for each subject and the orientation of each object (steel part to the left or right) was assigned randomly. Grasp positions (distance from steel end, as defined in Fig. 2A) were determined by identifying the centre of the contact regions of index finger and thumb with the object, and finding the center of the grasp axis between the two (see Fig. 2C). Note that determining the extent of the contact regions was aided by video, which showed deformation of the fingertips.

**General Methods: Participants**

Twenty participants completed Experiments 1-3, with 17 participants in Experiment 4 (all non-overlapping groups). All participants provided their gender by self-report. Experiment 1: 16 females, 4 males, mean age ± 1SD: 27 ± 7 years; Experiment 2 (A and B): 11 females, 9 males; 24.75 ± 5.6 years; Experiment 3 (A and B): 19 females, 1 male, 24.95 ± 5.6 years; Experiment 4: 7 females, 10 male, 25.7 ± 3.4 years. All participants had normal or corrected-to-normal vision and no reported motor deficits. In Experiments 1-3, all were right-handed and performed the task with the dominant hand. Experiment 4 included 10 right and 7 left-handers, who performed trials with each hand. Written consent was obtained before the experiment. The experimental procedures were approved by the University of Ulm ethics committee (application nr. 245/20). Data and analysis code can be downloaded here: https://doi.org/10.5258/SOTON/D3407.

**Experiment 1: Natural density materials and prior exposure.**

Experiment 1 employed the Natural Density stimulus set. Before the experiment, participants were asked to lift and briefly explore (approximately 15 seconds) two homogenous cylinders of uniform density: one made of steel and the other of PVC. These were 16cm long (i.e., half the length of the main stimuli). This provided participants with information about the two materials' densities. Participants then completed 45 trials (9 objects x 5 lifts per object) presented in pseudorandom order (object order was randomised within each repetition) in a single session, lasting approximately 30 minutes.

Data from Experiment 1 are shown in Fig. 3. Figure 3A displays all grasp points per object, pooled over participants, superimposed on a stimuli schematic. It is apparent that grasp positions on each observer's first trial (red dots: one per participant) are close to the objects' GC (dashed black line), whereas those on the final trial (green dots) are closer to the true centres of mass of the composite objects (blue lines). (Due to randomisation of stimulus order, it just so happened that objects 1, 4 and 8 were never presented first and objects 4 and 7 were never presented last in this Experiment). The learning trajectory is shown in Figs 3B and C. Figure 3B shows the mean raw data (red stars) and the model fit (black line – see description below) for all composite objects (i.e. objects 2-8). For plotting, data (and model fits) have been converted to normalised grasp location:

$$\text{Normalised grasp location} = (\text{Grasp location} - \text{GC}) / (\text{CoM} - \text{GC}) \qquad (1)$$

A normalised grasp location of 0 corresponds to the geometric centre, and a value of 1 corresponds to the objects' centre of mass. This conversion allows us to aggregate / compare grasping data across objects on a common scale. Data from objects 1 & 9 are excluded from these analyses as the grasping locations for these homogenous objects should be independent of the underlying assumed densities of the two materials. It is apparent that participants are grasping close the GC within the first few trials, and that learning asymptotes at positions that are roughly 80% toward the centre of mass. Note that observers cannot be learning where to grasp in world-centred coordinates because objects were presented in two different orientations.

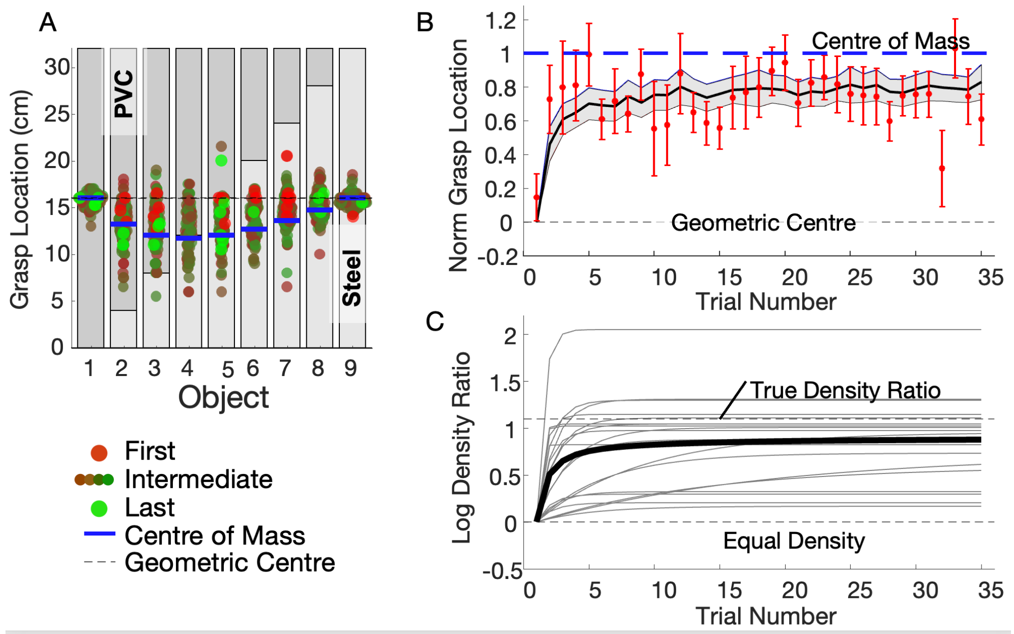


***Figure 3:*** *Experiment 1 Results.* ***(A)*** *Grasp positions pooled across participants. Red spots show the first grasp, i.e. trial = 1, green spots show the last grasp, and intermediate grasp points are shown according to the colour continuum. Centre of mass for each object is shown by a blue bar, with the geometric centre given by a dashed black line.* ***(B)*** *Raw data averaged across observers (N=20) with error bars showing ±1SE (red). The average fitted model (translated to equivalent normalising grasping location) is shown in black, with the shaded region representing ±1SE.* ***(C)*** *The underlying exponential learning of log density ratio for each observer (grey lines, one per observer) and their average (black line).*

## Modelling

It is clear from Fig. 3B that observers do not learn the CoM independently for each object. Instead, information gleaned on the first trial(s) is used to guide grasping closer to the CoM of novel objects from trial 2 onwards. Thus, observers must be learning something common to all objects - the ratio of the two components' densities - which, alongside visually-defined geometric information (i.e. the extent and location of the two components), determines the CoM for all objects. We take the *log* of the density ratio, as this has the same magnitude irrespective of which component is used as the denominator, and when the density relationship is reversed in Experiments 2 & 3. The log density ratio can be estimated following a single lift, using the mass and torque experienced for the selected grasp position, alongside the object geometry. Note that torque plus geometry gives only the *difference* between the two components' densities (not the ratio), and is thus not enough to determine the CoM, without object mass (see Supplementary Information, Section S2 for equations). To model the learning trajectory, we assume that observers (likely implicitly) update their estimates of the log density ratio: LDR = ln ($\rho_{Steel}$ / $\rho_{PVC}$) according to an exponential function (Cochrane & Green, 2021; Heathcote et al., 2000; Stratton et al., 2007)

$$\widehat{LDR} = \left(\widehat{LDR}_{start} - \widehat{LDR}_{end}\right)e^{-rt} + \widehat{LDR}_{end} \quad (2)$$

where $\widehat{LDR}_{start}$ is the initial estimate of log density ratio, $\widehat{LDR}_{end}$ is the asymptotic estimate of log density ratio after learning, $r$ is the learning rate and $t$ is the number of preceding trials (i.e. trial number -1).

The model assumes that before each grasp, the CoM for the newly encountered object is determined by the current estimated log density ratio, $\widehat{LDR}$, alongside the new object's geometry. Grasp locations are perturbed from this CoM location by random noise from a Gaussian distribution. The model fit to each observer's data had three free parameters: $LDR_{end}$, $r$ and $\sigma_N$, the standard deviation of the response noise. $LDR_{start}$ was fixed as 0, i.e. an initial assumption of equal density of the two components. The model was fit to each observer's data independently, using gradient descent (fminsearch, Matlab, (The MathWorks, 2023)) to find the parameters that maximised the likelihood of the data. We evaluated alternative models, e.g. those that included $LDR_{start}$ as a free parameter and / or noise in the estimate of $LDR$, or exponential learning of the raw (rather than log) density ratio, but these were rejected following model comparisons (see Supplementary Information, Section S3).

Figure 3C shows the exponential learning curves fitted to individual observers' data in Experiment 1 with the mean across observers in black. Observers' initial grasps were not significantly different from the GC (mean initial grasp = 15.4cm, GC=16cm, one sample *t*-test: $t_{19}$ = -1.4241, $p$= 0.17). Somewhat surprisingly, this suggests that observers' exploration of the two component materials before the main experiment did *not* guide their grasping on trial 1. It is also apparent that there is a great deal of individual variation in the amount of learning: some participants display near-perfect adaptation, as signified by $LDR$ close to the true log density ratio of 1.1, i.e., ln(3), corresponding to normalised grasping locations of ~1. Other participants show very little adaptation – their estimated log density ratio rose only slightly above 0, i.e., grasping positions stayed around the objects' geometric centres.

Figure 3B shows the exponential model fit, after converting $LDR$ to the corresponding estimated CoM, and from this to normalised grasping location. This conversion allows us to visualise the model alongside the grasping data for all objects. The relationship between log density ratio and normalised grasping position is slightly different for each object, resulting in a model fit that it not a smooth curve in this space (see Supplementary Information, Fig. S1).

Learning is, on average, fast, with a mean learning rate of 1.17, corresponding to a 52% shift towards the asymptotic log density ratio, on average, per trial. However, learning is also incomplete; on average, participants asymptote at grasping positions between the GC and CoM, corresponding to an average $LDR$ of 0.88, compared to the true value of 1.1.

**Interim Discussion**

In Experiment 1, participants initially grasped objects close to their GC. This is somewhat surprising, given that they had prior experience of the two materials' densities in isolation, and given previous findings that participants use visual density cues to explicitly estimate the CoM of composite objects similar to ours (Crajé et al., 2013; Paulun et al., 2019). On subsequent trials, participants did quicky adjust their grasp towards the CoM, reducing torque. This is in broad agreement with previous findings, that participants prefer grasp positions that reduce torque (Klein et al., 2020; Kleinholdermann et al., 2013; Lukos et al., 2007).

In Experiment 1, the component densities were consistent with participants' every-day experience of similar materials (i.e. PVC is generally 'lighter', i.e. less dense than metal) and also consistent with the properties of the component parts that they explored before the main experiment. In Experiments 2 & 3 we explore what happens when objects are encountered that differ from long-term and/or recent prior experience.

**Experiment 2: Natural and inverted density relationships**

Experiment 2 had two parts. Part A was identical to Experiment 1, with the exception that participants were not given the opportunity to explore the two component materials before the main task. This allowed us to identify whether the pre-exposure in Experiment 1 had any effect on grasping behaviour. As before, Part A employed the Natural Density stimulus set and participants completed 45 trials (5 repetitions x 9 objects, in pseudorandom order).

After Part A, participants left the room for a short break, during which, unbeknownst to them, the stimuli were switched to the Inverted Density set for Part B. This switch allowed us to explore how easily participants can adapt to new material properties, and moreover, whether learning is slower or less complete when these new materials are at odds with long-term prior experience.

The results of Experiment 2 are shown in Fig. 4A for Part A (left column) and Part B (right column). In Part A, grasping is initially near the geometric centre of the objects, before gradually shifting towards the centre of mass (corresponding to a log density ratio close to the true value of 1.1). In fact, grasp positions were significantly different from the GC on trial 1 (mean = 14.7cm, $t_{19}$=-3.1778, $p$<0.01 for $t$-test against GC) but were closer to the GC on trial 2 (mean = 15.1cm, $t_{19}$= -1.2061, $p$=0.24), suggesting the initial difference could be an anomaly. We note that, as in Experiment 1, model fits were not improved by fitting $\rho_{start}$ as a free parameter, rather than fixing it to reflect equal density, i.e., to predict grasping at the GC (see Supplementary Information, Section S3).

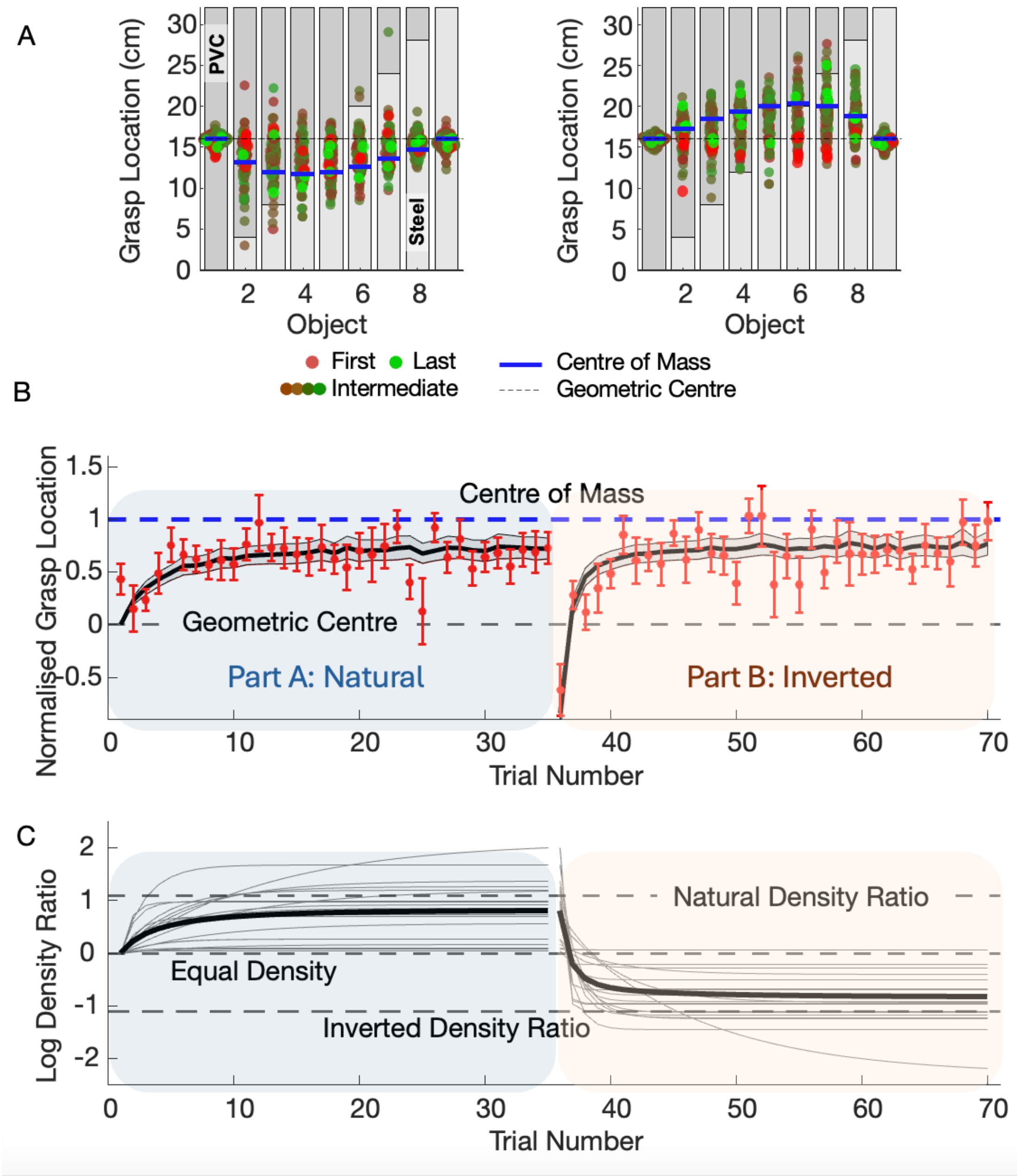


***Figure 4:*** *Experiment 2 Results.* ***(A)*** *Grasp positions pooled across participants in Part A (left) and Part B (right). Red spots show the first grasp, i.e., green spots show the last grasp, and intermediate grasp points are shown according to the colour continuum. The true centre of mass for each object is shown by the blue bars.* ***(B)*** *Raw data averaged across observers (N=20) with error bars showing ±1SE (red). The average fitted model (translated to normalising grasping location) is shown in black, with the shaded region representing ±1SE.* ***(C)*** *The underlying exponential learning of log density ratio for each observer (grey lines) and their average (black line).*

Comparison with Fig. 3 reveals that learning was slower on average in Experiment 2A than in Experiment 1, suggesting that although pre-exposure in Experiment 1 did not seem to affect the initial grasp, it may have expedited subsequent learning. Statistical comparisons between experiments are presented below in section 'Experiment comparisons'.

Participants were unaware of the stimulus switch before Part B, and this is evident in the data: there is clear carry-over from Part A of the learnt density relationship. The initial normalised grasp locations in Part B are well below 0 (mean = -0.62, one-sample *t*-test against 0: $t_{19}$= 2.5577, $p$<0.05, see Fig. 4B), and the initial grasp points (red dots) sit below the GC in Fig. 4A, right column. These initial grasping positions are well predicted by the model in which $LDR_{start}$ is assigned as the fitted $LDR$ from the final trial of Part A; allowing $LDR_{start}$ to be fit as a free parameter did not significantly improve the model fit (see Supplementary Information: Section S3). Verbal debrief after the experiment confirmed that participants were unaware of the switch and were surprised by the object properties on the first trial of Part B. We had hypothesised that learning may be slower in Part B, after the density relationship of the PVC and metal components was reversed. However, the opposite was observed – participants were very fast to adapt to the new stimuli to minimise torque (see Fig. 6 and below for cross-experiment comparisons).

**Experiment 3: Inverted and then Natural Density relationships**

Experiment 3 was identical to Experiment 2 except that the Inverted Density stimulus set was used in Part A, and then (secretly) swapped for the Natural Density stimulus set in Part B. This manipulation allowed us to explore the interaction of long-held assumptions with recent experience. If long-term experience significantly affects grasp planning, learning should be slower in 3A than in 2A (given the unnatural density relationship in 3A), but faster in 3B than 2B, when the stimuli revert to natural densities. (Different participants completed Expts 1, 2 and 3).

Figure 5 shows the results of Experiment 3. The pattern of learning is broadly similar to that for Experiment 2: in Part A, observers gradually shift their grasping positions from near the GC towards the CoM, but with incomplete adaptation, on average. Following the switch of stimuli (Part B) there is substantial carry-over of learning from Part A, which is followed by rapid adaptation to the new relative densities, i.e.

the new CoM positions. As in Experiments 1 & 2 there is substantial inter-subject variability, with some participants showing little adaptation to reduce torque.

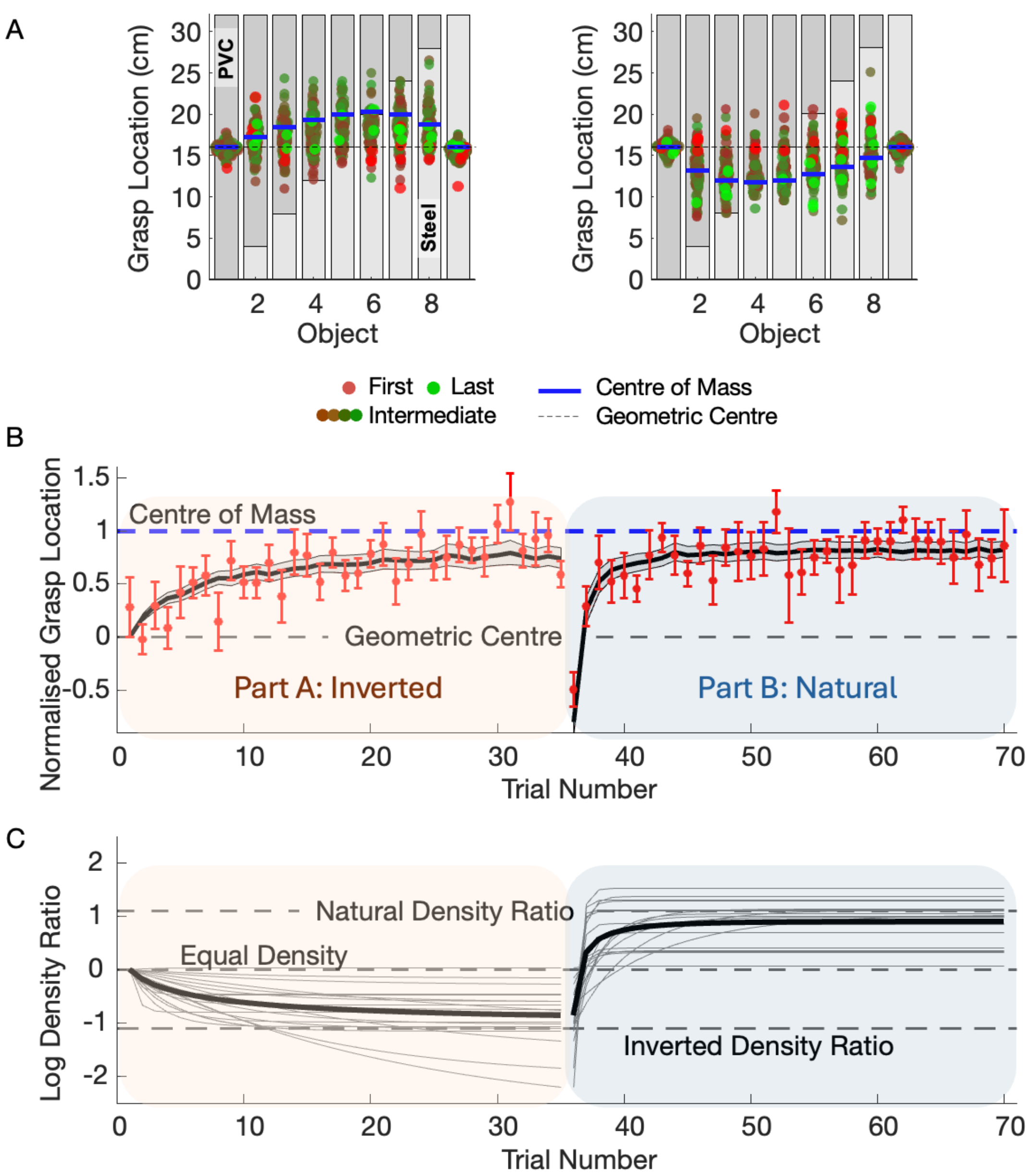


**Figure 5:** Experiment 3 Results, identical format to Fig. 4.

**Experiment comparisons**

We can directly compare the learning rates and extent of adaptation (i.e., the final fitted log density ratio / the true log density ratio) across Experiments 1-3, as shown in Fig. 6. The left-hand plot shows that learning rates varied substantially across experiments. To correct the skewed distributions, learning rates were log-transformed before ANOVAs and post-hoc comparisons. Learning differed significantly across

Expts 1, 2A and 3A ($F_{2,57}$=6.06, $p$<0.01; Bonferroni corrected post-hoc Expt. 1 vs 3A: $p$<0.01, see Supplementary Information S4). Thus, there is evidence that the short-term pre-exposure in Experiment 1 lead to faster learning, as learning was faster in Experiment 1 than 2A (but not significantly so) and significantly faster in Experiment 1 than 3A (despite 3A employing the Inverted Density stimulus set).

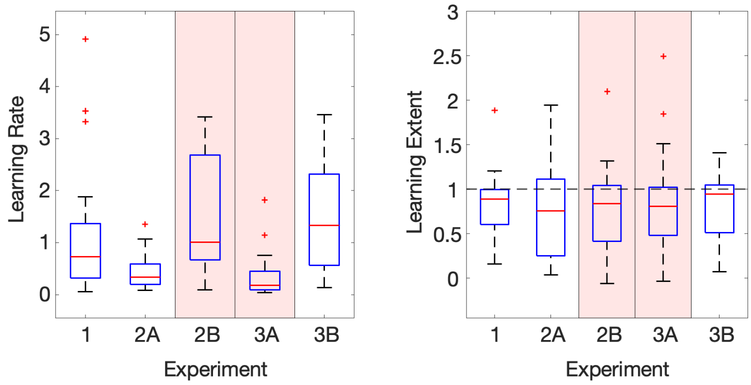


***Figure 6:*** *Learning rates (left) and the extent of adaptation (right) for Experiments 1-3. The dashed line shows full adaptation, i.e., final estimated log density ratio equal to the true value. Shaded pink areas show experimental conditions involving the Inverted Density ratio stimulus set.*

There is no evidence that long-term experience, i.e. that PVC is generally less dense than metal, had an impact on learning rate; there was little difference in learning rates between 2A and 3A, or between 2B and 3B (2 Factor ANOVA, part (A vs. B) x expt. (2 vs. 3), ns effect of expt: $F_{1,38}$=0.94, $p$=0.34, ns interaction expt. x part: $F_{1,38}$=2.1, $p$=0.15). Interestingly, learning was significantly *faster* following the surreptitious change of stimulus set between 2A and 2B and between 3A and 3B (Bs significantly faster than As: $F_{1,38}$=48.6, $p$<0.001). As noted above, participants were surprised following their first interaction with the new set of stimuli, and it is possible that this awareness of a stimulus change caused more rapid learning, akin to the 'oops' effect described in a different visual-haptic learning paradigm (Adams et al., 2010).

We can compare *object-level* adaptation of grasping position across experiments. Figure 7 shows the mean grasping position per object within different time windows. Because trial order was independently randomised for each subject, only a small number of participants lifted each object on each trial (average = 2.8). Given the large inter-observer variability (in addition to within-observer noise), we pool data across a 4-trial window to reveal per-object grasping trajectories. Data are noisy (in part because a different subset of participants is represented by each data point), but it is nonetheless clear that participants are already learning object-specific grasping positions in early trials. Shaded green areas show windows where the grasping pattern across objects within the trial window was significantly correlated ($p<0.05$) with the asymptotic grasping locations (i.e., averaged across trials 15-35) for the same subset of participants. These asymptotic grasping positions (averaged across all observers) are shown on the right-hand side of each plot.

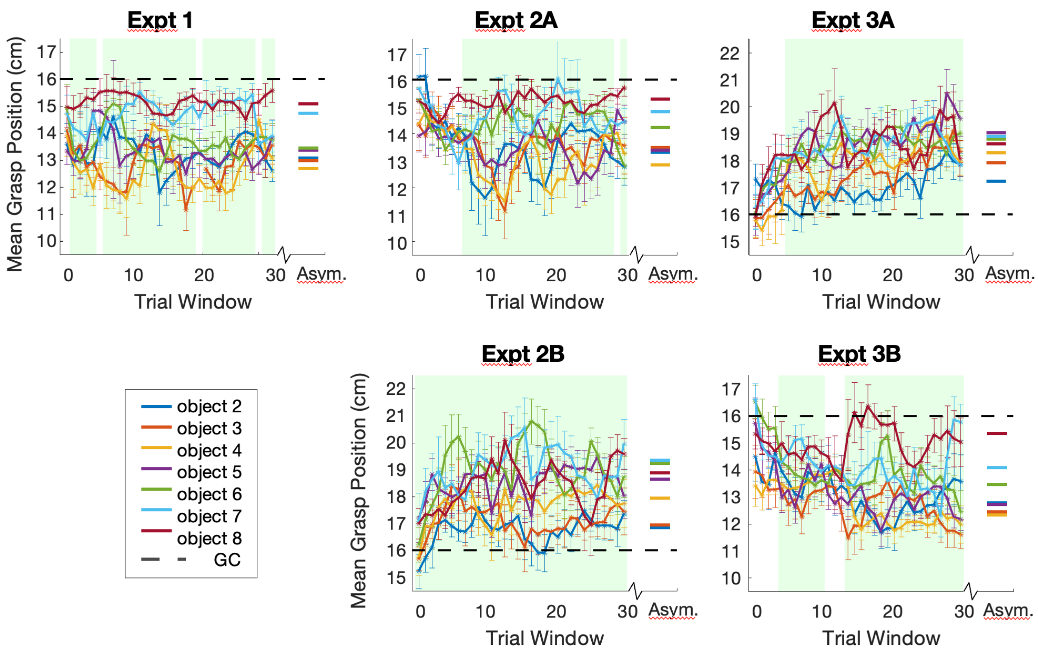


*Figure 7: Grasping trajectories for individual bipartite objects 2-8. Each subplot shows a different experiment. Each trial window pools data across subjects and across 4 trials: window 1 = trials 1 to 4, window 2 = trials 2 to 5, etc.. Each line colour shows a different object, and the horizontal dashed line shows the GC. Green shaded regions show epochs where there is a significant correlation (p<0.05) between the grasping positions in the current epoch and the asymptotic grasp points (defined as the average grasping position per object across the last 20 trials for the same subset of observers). These asymptotic grasping positions (averaged across all observers, "Asym.") are shown to the right of each plot. Error bars are ±1SE across observations.*

In Experiment 1, grasp positions on trial 1 did not differ from the geometric centre. However, Fig. 7 shows that differentiated grasp positions emerged very early – within the first 5 trials – i.e., before any stimuli had been repeated. This suggests that participants were almost immediately estimating the CoM across objects by combining density information with object geometry. In Experiments 2 & 3, the object-by-object grasping pattern is detected later (trial window 8 and 6, respectively). This might reflect greater response noise due to uncertainty in the learnt density relationship, or some early generalised learning, e.g. metal side is denser (Expt. 2), or the PVC side is denser (Expt. 3), within the first few trials. The slightly earlier emergence of a differential grasping pattern in Experiment 1 is in broad agreement with the evidence from learning rates (Fig. 6); pre-exposure to the stimulus materials seems to have facilitated learning *after* trial 1. Participants seemingly used trial 1 (consciously or unconsciously) to determine whether information gleaned from the homogenous pre-exposure objects was valid.

An object-by-object grasping pattern emerged very early – within the first 4 trials – in Experiment 2B (slightly later in 3B). Although the absolute CoM positions were very different for the 'Normal' and 'Inverted' set of stimuli, the pattern *across objects* was partially correlated. Thus, it is possible that this pattern partially transferred from Part A to Part B. Alternatively, as mentioned above, the large / unexpected force-feedback following the stimulus switch may have triggered fast adaptation to the new material densities.

In all experiments, participants failed (on average) to show complete adaptation; see Fig. 6B: data sit below the dashed line at 1. In other words, participants did shift their grasping towards the CoM, but not completely, and thus continued to experience systematic torque. This 'undershoot' was significant for Experiment 1 ($t_{19}$= -2.16 , $p$<0.05), Experiment 2a ($t_{19}$=-2.26, $p$<0.05) and Experiment 3b ($t_{19}$=-2.20, $p$<0.05). Our stimuli were fairly light (Natural Density set: 68-204g, Inverted set: 164-492g) and thus it is possible that we would have seen more complete adaptation with heavier objects (producing higher torque when grasping away from the CoM). Alternatively, decreasing friction (e.g. by adding a lubricant) may enhance adaptation by increasing the effects of torque. Previous authors have suggested that, since torque varies little with grasp position for lighter objects, it becomes a weaker predictor of contact point selection (Klein et al., 2020; Kleinholdermann et al., 2013). By this logic, we should have seen more complete adaptation with the heavier, Inverted Density set but this was not observed.

By comparing grasp positions for the two stimulus orientations (orientation 1: metal part on the left; orientation 2: metal part on righthand side) we can see that this manipulation modulates observers' underestimation of the true CoM (Fig. 8). Object orientation systematically affected the grasping position, shown here in object-centred co-ordinates; 2 factor ANOVAs (object x orientation) for each experiment confirmed that this orientation effect was significant ($p<0.01$ for Experiments 1, 2A, 3A, 3B, $p<0.05$ for Experiment 2B, see Supplementary Information S5). This translates to a bias in world-centred co-ordinates such that grasping was biased towards the object's right-hand end, i.e. an apparent bias to under-reach, which could be a strategy to minimise energy expenditure (Huang et al., 2012; Kleinholdermann et al., 2013). All participants in Experiments 1-3 were right-handed and performed all trials with their right hand.

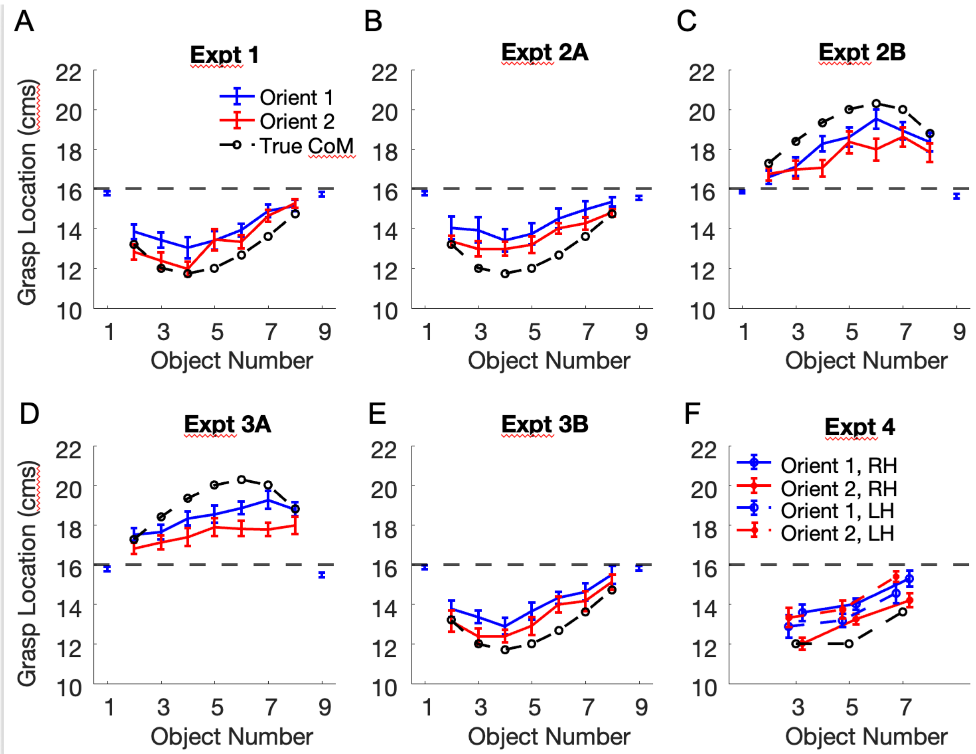


***Figure 8:*** *Effect of object orientation. Each subplot shows a different experiment. Blue and red show grasp positions (distance from metal end for objects 2-8; distance from left-hand end for objects 1, 9) for the different object orientations, for each object. The true CoM is shown in black. Horizontal dashed lines give the geometric*

*centre. Bottom right plot shows results of Experiment 4, plotted according to object orientation, and the hand used for grasping (RH, LH).*

**Experiment 4: Control experiment to examine hand-related biases**

To test our interpretation of the bias shown in Fig. 8a-e, we conducted a fourth experiment that involved a mixture of right and left-handed participants, and a subset of the Natural Density stimulus set (objects 3, 5 & 7). These participants performed half of the trials with their left hand and half with their right hand, for a total of 60 trials (3 objects x 2 orientations x 2 hands x 5 repetitions). Left- and right-handed grasping trials were blocked, with trial and block order randomised across participants. The results are shown in Fig. 8f. It is clear that the same pattern of bias is seen under right-handed grasping (solid lines, blue above red), whereas the bias pattern reverses when the same observers use their left hand (dashed lines). A 3 factor ANOVA (object x orientation x hand) confirmed a significant interaction between object orientation and grasping hand ($F_{1,16}$=30.8, $p$<0.001). This pattern of bias is consistent with our hypothesis, that participants systematically 'under-reach'; objects are grasped closer to their left-hand end when grasping is done with the left hand. As in the main experiments, we can also see evidence of incomplete adaptation to the true density ratio; grasping is between the CoM and the geometric centre (dashed horizontal line).

**General Discussion**

We conducted four experiments in which participants picked up cylindrical objects made of varying proportions of steel and PVC, using a precision pincer grip, and placed them on a stand. As grasp point selection was unconstrained, we were able to observe the changes in grasp location over trials to infer how participants use visuo-haptic cues along with prior knowledge to adapt their grasping behaviour. Across all experiments, participants' initial grasps were close to the objects' geometric centres (GC) and over trials, grasp positions moved closer to the objects' center of mass (CoM). Participants did not apply prior knowledge of material densities on the first grasp but quickly learned it through iteration. This learning transferred to other objects within the stimulus set that had different proportions of the two materials.

*How are initial grasp points selected?*

Participants initially grasped the objects close to the GC, apparently guided by visual cues to object size and shape, under the assumption that the two components have equal density. Indeed, it has previously been suggested that grasping at the GC may be a default strategy when the CoM is unknown (Lukos et al., 2007). However, our participants had access to material density cues that could have allowed them to achieve more accurate estimation of the CoM: visual material cues (all experiments), and in Experiment 1 observers also explored the individual materials before the experimental trials.

If lifelong experience with familiar materials was exploited when grasping novel composite objects, participants' initial grasps should have been biased away from the GC towards the true CoM, i.e. towards the apparently denser (metal) side of the object. Previous work, with similar bipartite objects, shows that participants do use such material density priors cues to guide CoM estimates when the CoM is explicitly estimated (Crajé et al., 2013; Lee-Miller et al., 2016; Paulun et al., 2019). Why does this not translate to grasping behaviour? In Crajé et al. (2013), grasping *position* was constrained, but grasping *forces* were measured. On initial trials, participants did not modulate anticipatory grip forces (i.e. to create a compensatory moment) to counteract expected torque in bipartite objects. In contrast, for homogenous objects, anticipatory grip forces were modulated by the object's total expected weight (given the apparent material), consistent with previous studies of the material weight illusion (see below). In Lee-Miller et al. (2016), grasping was also constrained to a vertical handle above the bulk of the object (an inverted T shape), but the grasping surface was vertically extended. Participants introduced a small vertical offset between finger and thumb on trial 1 but used a much larger offset by trial 10. (But note that participants were explicitly instructed to avoid object roll in this study).

The only effect of prior experience that we observed was the faster learning rates of Experiment 1, after participants explored homogenous cylindrical objects with the same materials as the subsequent objects. This suggests that recent experience of the material densities may facilitate subsequent *speed* of grasp point adaptation.

Our study reveals that the dichotomy between explicit estimates of CoM and initial grasping behaviour persists even in a more naturalistic, unconstrained grasping task. Why would such a dichotomy arise? There have been suggestions of a broader neurophysiological perception-action disconnect (Goodale & Milner, 1992). However, a more ecological account might assume that the two tasks involve very different costs: There is no error cost in the explicit estimation task. In a grasping task, however, there is a potential cost of instability / object roll (and possible drop) if the visual density cues turn out to be misleading (see below).

*Contrast with homogenous objects (e.g., the material-weight illusion).*

As noted above, participants do scale anticipatory grip forces according to the apparent material of an object (Crajé et al., 2013). Indeed, this has been proposed to explain the material-weight illusion (MWI). The MWI occurs when subjects lift two equal-sized objects made of apparently different materials (e.g., wood and brass) that in fact have equal weight. Upon lifting, the heavy-looking object is perceived as *lighter* than the lighter-looking object (Buckingham et al., 2009; Ellis & Lederman, 1999; Seashore, 1899). One explanation is that, because greater grip and load forces are applied to the heavier-looking object, it is lifted faster and more easily than anticipated. However, note that, as in the size-weight illusion (Flanagan & Beltzner, 2000), the illusion persists after force adaptation (Buckingham et al., 2009), although see Harris et al. (2024). Learning a new size-weight relationship (an inverted illusion) after density manipulations follows a much slower learning trajectory (days or weeks) compared to the rapid adaptation of grip forces within a few trials (Flanagan et al., 2008).

*Learning trajectory*

Previous studies have shown that, within a session of many trials, actors use grasp points that reduce torque (Klein et al., 2020; Kleinholdermann et al., 2013; Lukos et al., 2007) and adjust their grasping forces to counteract torque (Crajé et al., 2013). However, these studies did not reveal *how quickly* grasp point adaptation occurs. We show that the majority of learning occurs following the very first trial, on experiencing the mass and torque of a stimulus, and that this fast learning occurs without explicit instruction to eliminate object rotation. Studies in other domains have shown evidence of perceptual priors that form over lifelong experience but remain adaptable in response to long-term visual-haptic learning (Adams et al., 2004; Champion & Adams, 2007; Flanagan et al., 2008; Kerrigan & Adams, 2013). Kording et al. (2007) and Burge et al. (2008) suggested that states considered (perhaps implicitly) to be probabilistically transient or short-term should be easily adapted, while states which are likely more stable over time should be slower to adapt. Alternatively, priors may be updated / over-ruled only within a particular environmental context (Kerrigan & Adams, 2013).

Our study suggests that density priors are easily adaptable, broadly in line with fast adaptation of grasp and load forces in the MWI (Buckingham et al., 2009). In fact, we failed to see faster learning in our Natural Density condition than the Inverted one, suggesting very little influence of visually-derived density priors. One possible reason for the rapid updating of material density priors may be the high degree of uncertainty (i.e. a weak correlation) in the relationship between the look of an object and its density distribution: objects may be only coated with the material visible on the outside, such that they are primarily composed of a more or less dense material, or they might be hollow. Uncertainty in this appearance-density distribution relationship may be increased in multi-material objects such as those used in this experiment. One reason the material-weight-illusion is much weaker than the size-weight-illusion (Buckingham, 2014) may be the high uncertainty between the look of the material and its weight compared to its size-weight relationship; the size-weight illusion may, in part, relate to an assumption that similar-looking objects that are presented side-by-side will have the same size-weight relationship (although see Pisu et al. (2024) for discussion of different SWI models).

The fast learning that we observe, particularly in Experiment 1, also indicates that observers are applying material density information from one object to determine the CoM of others in the set. It remains somewhat puzzling that pre-exposure to the two materials within homogenous objects in Experiment 1 did not transfer to the initial grasp location for the stimulus objects – participants apparently did not initially trust that the materials were the same. It is worth noting that Crajé et al. (2013) also found that pre-exposure to object components failed to modulate initial grasping forces.

*Is torque the only cost function at play?*

When selecting a grasping posture and position, various cost functions, in addition to torque minimisation are at play. These include (i) force closure: the grasping surfaces should be (close to) parallel, with gripping forces directed towards each other, although this can be relaxed when friction is greater (Blake et al., 1992; Chen & Burdick, 1993; Iberall et al., 1986; Nguyen, 1986) (ii) biomechanical comfort, which promotes the natural grasp axis (Lederman & Wing, 2003) and the natural grasp aperture (Cesari & Newell, 1999), (iii) end state comfort (Rosenbaum et al., 1999) and (iv) minimal grasping movement, i.e. a preference for grasp locations closer to the grasping hand (Kleinholdermann et al., 2013).

Kleinholdermann et al. (2013) and Klein et al. (2020) have shown that torque minimisation is combined with these other constraints to guide grasp point selection. In the present study, we would expect participants' asymptotic grasp positions to be at the CoM, on average, if torque were the only cost function involved. However, this was not observed; two small but stable biases were observed. A bias towards the GC was evident in all experiments (see Fig. 6b). Such biases have previously been described as a "symmetry prior" (Lukos et al., 2007). Another possibility is that observers do not fully adapt their estimates of material density to the true values, instead 'holding on' to the assumption that the two materials' densities are (or may revert to) being more similar, akin to regression to the mean in conditions of uncertainty. In fact, there was substantial inter-observer variation in the extent of adaptation, with some participants continuing to grasp near to the GC, on average.

In addition, we saw a bias in which grasp positions were closer to the grasping hand. Similar biases have been observed previously (Huang et al., 2012; Klein et al., 2020; Kleinholdermann et al., 2013; Paulun et al., 2016) and may reflect a trade-off between reducing torque and reducing the size of the arm movement (and thus energy expended) to grasp the object. Logically, this trade-off should depend on object weight, because lighter objects produce less torque. We might, therefore, expect a smaller grasping undershoot for the heavier (greater torque) Inverted Density set, but this was not observed.

Kleinholdermann et al. (2013) found that torque minimisation played a significant but very small role in grasp point selection, when competing with other factors (force closure, natural grasping axis) in a set of relatively light (38-89g) objects. Similarly, Klein et al. (2020) found that torque was not minimised via grasping position in a set of lighter objects (97g). They did find an effect of torque for heavier objects (716g) but the increase in weight was confounded with an additional instruction to keep objects level. Paulun et al. (2016) found that the magnitude of grasping undershoot is correlated with object mass in homogenous cylinders, suggesting a trade-off between different costs. We did not, however, see the same difference between our homogenous objects of steel and PVC (i.e., objects 1 and 9).

Paulun et al. (2014) have suggested that the cause / benefit of under-reaching may not be cutting energy costs, but the maximisation of object visibility (i.e. minimising occlusion by the hand). With our relatively wide stimuli, and absence of grasping positions near the stimulus ends, maximising visibility is unlikely to explain our observed pattern of orientation-related bias. Another possibility is that, in the presence of uncertainty about the true CoM, the 'undershoot' may reflect a strategy to limit object rotation: if the true CoM is away from the hand, the object's rotation will be blocked by the palm.

Overall, it seems likely that torque minimisation drives grasping position, but in competition with other costs and constraints. However, it is less clear to what extent this trade-off is modulated by object weight, or weight distribution.

## Conclusion

Human grasping behaviour suggests that we place little trust in visual cues to predict material density; initial grasps of a newly encountered set of objects reflect an assumption of equal density which manifests as a preference for grasping objects at their geometric centres. On the other hand, there appears to be a strong expectation that within a set of objects, material densities will be consistent: generalised learning occurs rapidly. Upon encountering evidence (mass, torque from a single lift) that the object set has changed, adaptation is expedited, and previous experiences are disregarded. Torque minimisation is clearly a strong driver of in the choice of grasp location. However, stable biases away from the centre of mass suggest that other cost functions are also influential in selecting the optimal grasping points.

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**<u>Supplementary Information for "Grasping New Material Densities".</u>**

## S1. Relationships between log density ratio, centre of mass, object mass and torque.

The object's CoM depends on the geometric centres of the two components ($GC_{Steel}$, $GC_{PVC}$), the density of the two materials ($\rho_{Steel}, \rho_{PVC}$) and their volumes ($Vol_{Steel}, Vol_{PVC}$):

$$CoM = \frac{GC_{Steel} \times Vol_{Steel} \times \rho_{Steel} + GC_{PVC} \times Vol_{PVC} \times \rho_{PVC}}{Vol_{Steel} \times \rho_{Steel} + Vol_{PVC} \times \rho_{PVC}}$$

More simply, the CoM can be determined from the ratio of the two densities, i.e. let $\rho_{Steel} = k \times \rho_{PVC}$

$$CoM = \frac{GC_{Steel} \times Vol_{Steel} \times k \times \rho_{PVC} + GC_{PVC} \times Vol_{PVC} \times \rho_{PVC}}{Vol_{Steel} \times k \times \rho_{PVC} + Vol_{PVC} \times \rho_{PVC}}$$

$$= \frac{GC_{Steel} \times Vol_{Steel} \times k + GC_{PVC} \times Vol_{PVC}}{Vol_{Steel} \times k + Vol_{PVC}}$$

Similarly, only the ***ratio*** of the two volumes (or the ratio of the two lengths, given that length ∝ volume for cylinders) is required to determine the CoM. Let $Length_{Steel} = l \times Length_{PVC}$, then

$$CoM = \frac{GC_{Steel} \times Length_{PVC} \times l \times k + GC_{PVC} \times Length_{PVC}}{Length_{PVC} \times l \times k + Length_{PVC}}$$

$$CoM = \frac{GC_{Steel} \times l \times k + GC_{PVC}}{l \times k + 1}$$

As the LDR increases or decreases, the object's CoM asymptotes to the GC of one of the two components:

$$As\ LDR \to \infty,\ \ k \to \infty,\ \ CoM \to \frac{GC_{Steel} \times l \times k}{l \times k} = GC_{Steel}$$

$$As\ LDR \to -\infty,\ \ k \to 0,\ \ CoM \to \frac{GC_{PVC}}{1} = GC_{PVC}$$

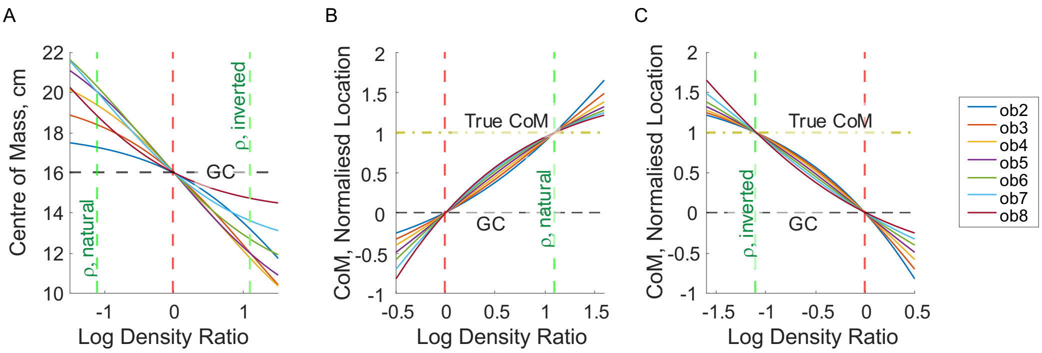


***Figure S1.*** *Log density ratio and centre of mass.* ***(A)*** *Relationship between the log density ratio and each object's centre of mass, in cm.* ***(B)*** *Natural Density stimuli: the relationship between log density ratio and the CoM, in units of normalised location.* ***(C)*** *Inverted Density stimulus set. The normalised location metric allows us to combine grasping data from different objects within a common scale.*

## S2. Estimation of material densities (or their ratio) from the forces experienced on lifting the object.

The torque, $\tau$, experienced on lifting a stimulus object depends on the grasp position (*Grasp*), the geometric centres of the two components, their volume, and density:

$$\tau = (GC_{Steel} - Grasp) \times Vol_{Steel} \times \rho_{Steel} + (GC_{PVC} - Grasp) \times Vol_{PVC} \times \rho_{PVC}$$

The total object mass depends on the volume and density of the two parts:

$$Mass = Vol_{Steel} \times \rho_{Steel} + Vol_{PVC} \times \rho_{PVC}$$

Rearranging these equations gives:

$$\rho_{PVC} = \left(Mass - \frac{\tau}{(GC_{Steel} - Grasp)}\right) / Vol_{PVC} \times \left(1 - \frac{(GC_{PVC} - Grasp)}{(GC_{Steel} - Grasp)}\right)$$

$$\rho_{Steel} = (Mass - \rho_{PVC} \times Vol_{PVC}) / Vol_{Steel}$$

Note that if $Length_{Steel}$ *and* $Length_{PVC}$ are substituted for $Vol_{Steel}$ *and* $Vol_{PVC}$, the ***ratio*** of the two densities will remain correct.

## S3: Model details

Fitted parameters: means and (std) for the preferred model (Model 1). Subsequent columns show the parameters of alternative models (p1-p4) and how these compare to the preferred model.

| Model | 1 | | | | | | 1_lin | 2 | 2_lin | 3 | 3_lin | 4 | 4_lin |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Exp1 | Exp 2A | Exp 2B | Exp 3A | Exp 3B | | | | | | | |
| $LDR_{start}$ | 0 | | | | | | 0 | 0 | 0 | 0 | 0 | p1 | p1 |
| $LDR_{end}$ | p1 | 0.88 (0.44) | 0.81 (0.56) | -0.8 (0.55) | -0.93 (0.65) | 0.90 (0.40) | p1 | p1 | p1 | p1 | p1 | p2 | p2 |
| $r_A$ | p2 | 1.17 (1.31) | 0.44 (0.34) | 1.46 (1.15) | 0.36 (0.44) | 1.50 (1.04) | p2 | p2 | p2 | p2 | p2 | p3 | p3 |
| $\sigma_N$ | p3 | 1.58 (0.39) | 1.70 (0.80) | 1.78 (0.63) | 1.60 (0.47) | 1.68 (0.55) | p3 | p3 | p3 | 0 | 0 | p4 | p4 |
| $\sigma_{LDR}$ | 0 | | | | | | 0 | p4 | p4 | p3 | p3 | 0 | 0 |
| Log likelihood | | 133.9 (11.2) | 135.1 (15.3) | 136.9 (15.6) | 133.6 (14.2) | 136.1 (14.2) | | | | | | | |
| Learning space | log | | | | | | linear | log | linear | log | linear | log | linear |
| N subs preferred | | | | | | | 6, 9, 5, 13, 7* | 0, 1, 0 | 0, 0, 0 | 5, 6, 2 | 5, 4, 1 | 3, 5, 7, 1, 5 | 5, 2, 4, 5, 5 |
| vs. model | | | | | | | 1 | 1 | 1_lin | 1 | 1_lin | 1 | 1_lin |

***Table S1**. Model parameters and comparisons. Model 1 is the preferred model, presented in the manuscript. The fitted parameters (those maximising the log likelihood of the data) are presented for each experiment part. Alternative models are presented in terms of the free parameters and the learning space, i.e., whether learning of density ratio followed exponential trajectory in log space, i.e. log($\rho_{steel}$ /$\rho_{PVC}$) or linear space (shaded columns). For each alternative mod, N subs preferred gives the number of subjects (of 20) for which the alternative model was preferred. For models of equal complexity (e.g. 1 vs 1_lin), this is simply a comparison of log likelihoods. For models of different complexity, the comparison was made via F ratio tests. N subs preferred is given either for (i) Expts. 1, 2A, 2B, 3A and 3B or (ii) only for Expts. 1, 2A and 3A. *Note that there was little difference in log likelihood between model 1 and model 1_lin: less than 1% for all subjects.*

**S4. Post-hoc comparisons for learning rate, following ANOVA, as shown in Fig. 6A**

| Group 1 | Group 2 | Mean Difference | Upper CI | Lower CI | p-value |
|---|---|---|---|---|---|
| Expt 1 | Expt 2a | 0.6363 | -0.2484 | 1.5211 | 0.274 |
| Expt 1 | Expt 2b | -0.4577 | -1.3425 | 0.427 | 0.6045 |
| Expt 1 | Expt 3a | 1.1439 | 0.2591 | 2.0287 | 0.0046 |
| Expt 1 | Expt 3b | -0.5307 | -1.4154 | 0.3541 | 0.4585 |
| Expt 2a | Expt 2b | -1.0941 | -1.9788 | -0.2093 | 0.0076 |
| Expt 2a | Expt 3a | 0.5076 | -0.3772 | 1.3923 | 0.5041 |
| Expt 2a | Expt 3b | -1.167 | -2.0518 | -0.2823 | 0.0036 |
| Expt 2b | Expt 3a | 1.6016 | 0.7169 | 2.4864 | 0 |
| Expt 2b | Expt 3b | -0.073 | -0.9577 | 0.8118 | 0.9994 |
| Expt 3a | Expt 3b | -1.6746 | -2.5593 | -0.7898 | 0 |

**S5. ANOVA details for orientation effect, as shown in Fig. 8**

Separate 2 factor repeated measures ANOVAs (object x orientation) per experiment show significant effects of both object and orientation on grasping position within each experiment.

Expt. 1: Effects of object: $F_{6,266}=13.0$, $p<0.001$ and orientation: $F_{1,266}=7.2$, $p<0.01$
Expt. 2A: Effects of object: $F_{6,266}=5.5$, $p<0.001$ and orientation: $F_{1,266}=7.6$, $p<0.01$
Expt. 2B: Effects of object: $F_{6,266}=6.0$, $p<0.001$ and orientation: $F_{1,266}=5.71$, $p<0.05$
Expt. 3A: Effects of object: $F_{6,266}=3.7$, $p<0.01$ and orientation: $F_{1,266}=19.4$, $p<0.001$
Expt. 3B: Effects of object: $F_{6,266}=8.8$, $p<0.001$ and orientation: $F_{1,266}=8.3$, $p<0.01$