Influence of Form and Motion on Biological Motion Prediction

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Abstract

Perceiving and predicting the actions of other biological agents is essential for survival and social interaction. Recent studies have found that amount of motion exposure and motion kinematics are important for making predictions about human actions. In this study, we investigated how object form and amount of motion exposure contribute to action prediction. We used biological and nonbiological objects moving with biological motion. This motion profile is expected for biological objects, but not nonbiological objects. We also manipulate amount of motion exposure. We hypothesized that people should make more sensitive predictions for the biological object since its form and motion are congruent. Furthermore, this benefit should be especially pronounced at short periods of motion exposure. In Experiment 1, we used a task that allowed us to fit psychophysical curves and used a human hand for the biological object and an oval for the nonbiological object. We found that people were equally sensitive for the human hand and oval, and that there was an increase in sensitivity for longer motion exposures. For Experiment 2, we changed the task so that we could analyze both sensitivity and response bias, and we changed the nonbiological object to be a robot hand. We found that people were equally sensitive to the human hand and robot hand, but people were more biased to respond "congruent" to the human hand than robot hand. Prime duration affected both sensitivity and response bias. We conclude that prime motion duration affects low-level motion perception processes, while the object form affects high-level decision making processes.

1 Introduction

Perceiving and predicting the actions of other biological agents is essential for survival and social interaction. In this set of experiments, we investigate how people make predictions about moving objects, looking specifically at the role of object form information and amount of motion exposure.

The first piece of evidence humans and monkeys perform predictive processing of actions was from monkey mirror neuron studies. Mirror neurons are neurons that fire both when a monkey performs an action and when it observes another agent performing that action (Rizzolatti, Fadiga, Gallese, & Fogassi, 1996). Umilta et al. (2001) recorded from mirror neurons while the monkey observed a human hand move and disappear behind an occluding wall. They found that a subset of the mirror neurons responded both when the hand was in view and also when it was behind the occluder. This suggests that there are representations of the motion that are retained in the brain. In a recent human electrophysiological study, Saunier et al. (2013) presented participants with either an intact or scrambled point-light actor (PLA) performing an action. Then the PLA would be occluded by a large box on the screen either at a predictable or unpredictable time. They found that when the occlusion point was predictable, there was a difference in ERPs between the intact and scrambled conditions. But when the occlusion point was unpredictable, there were no differences in the ERPs between the intact and scrambled conditions. This suggests that when people expect an object to disappear at a particular point and the object's movement is predictable, there is a circuit recruited to keep motion permanence during the occlusion, and furthermore the object must have a coherent global motion in order to be processed during the occlusion.

Early human behavioral studies were the first to suggest that perception of actions is crucially dependent on knowledge and experience with human body movements. In general, when presented with pictures that suggest apparent motion, people are most likely to perceive that the movement took the shortest path possible through the two frames. But Shiffrar and Freyd (1990) and Shiffrar and Freyd (1993) showed that when people view pictures of humans and do this task, they are more likely to conclude that the motion went through a longer path when the shortest path is biomechanically impossible or implausible, especially when given a long lag time between presentation of the two pictures. This began to hint that people use their knowledge of how human bodies are likely to move during action perception.

Recently, experiments have begun to more explicitly test how people make predictions about actions. There are many variations on this paradigm. For example, Aglioti et al. (2008) investigated how elite and novice sports players make predictions about whether a particular sports action will be successful (in this case, whether a basketball player will make a free throw shot or not). Participants are presented with the beginning of an action, and then it is occluded after a variable amount of time. Participants then judge whether or not the action will be successful. The general conclusions from this literature are that the motion kinematics of the hand, wrist, and knees are crucial for making predictions, and that experts are more able to utilize these cues than novices (see Farrow et al., 2005 for a more thorough review).

More recently, the occlusion paradigm has given researchers an even finer-grained measure of how people make predictions. For example, Pozzo et al. (2006) showed subjects a dot moving up or down, and then it is occluded and subjects use a mouse click to indicate where they think the object will stop (point estimate), or press a button when they think the object will stop moving (time estimate). However, the occlusion paradigm that most studies use is adapted from Graf et al. (2007). In this paradigm, subjects see an object moving across the screen for a variable amount of time (prime motion), and then the object is occluded by a large box across the screen (occlusion period). Then, the object reappears and it either reappears at the correct point, or at some offset point along the same trajectory. After the trial, subjects have to make some kind of judgment about the reappearance (usually, whether or not the reappearance point was correct).

The general consensus from such occlusion paradigm studies is that motor simulation appears to be crucially involved in making predictions about moving objects. For example, Stadler, Ott, et al. (2012) found that when the dorsal premotor cortex, a region thought to be crucial in motor simulation, is suppressed via repetitive TMS participants have higher error rates in an occlusion paradigm task. Pozzo et al. (2006) and Saunier et al. (2008) show that in simple and complex motions, subjects make better point estimates for objects that move with biological motion than nonbiological motion. Similarly, Stadler, Springer, et al. (2012) show that participants have lower error rates in an occlusion paradigm for point-light actors (PLAs) moving with biological than nonbiological motion. Springer and Prinz (2010) further suggest that motor simulation is crucially involved with prediction by showing that processing an action verb while doing an occlusion paradigm task leads to higher error rates than when processing a verb that does not denote an action.

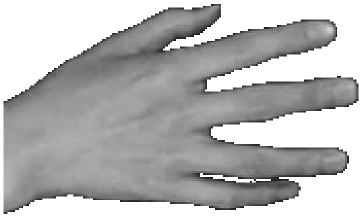
Saygin and Stadler (2012) looked at how form influences action prediction in the occlusion paradigm. They used natural videos of three agents: human, robot, and android (the android's movements are identical to the robot but the form looks like a human). They found that people were equally accurate for all of the agents in congruent trials. However, there were differences in accuracy for the early and late trials. On early offset trials, subjects were more accurate with the human and android agents than the robot agent. On late offset trials, subjects were more accurate with the robot than the human and the android. This suggests that the form of the agent matters for action prediction: nonbiological forms show an accuracy advantage at late offsets, and biological forms show an accuracy advantage at early offsets. However, it is important to note that both the form and the motion was different between these agents, so it is not completely clear whether we can make conclusions about form and motion separately.

It has also been shown that amount of motion exposure is also crucial when making predictions about actions. Parkinson, Springer, and Prinz (2012) manipulated the duration of the prime motion and duration of reappearance motion in two separate experiments, and found that both affected how people make predictions. In particular, a longer prime motion duration leads to higher sensitivity, and a longer reappearance motion duration leads to a perception that the offset which is congruent is closer to 0 (where 0 is the objectively congruent offset value).

Taken together, these occlusion paradigm studies have shown that both motion type and amount of motion exposure are very important for action prediction. However, the role of object form is less clear. There is evidence from the monkey mirror neuron literature that monkeys simulate both human and mechanical (i.e., robot) actions (Gazzola et al., 2007). This suggests that humans should be able to make accurate predictions about a variety of different objects. However, we were interested in looking at how people make predictions when the form of the object and its motion are incongruent. In this set of experiments, we use the same occlusion paradigm adapted from Graf et al. (2007). We use either a human or non-human object moving with biological motion. For the human object, the biological motion should be congruent with its form, but for the non-human object, its motion will be incongruent with its form. We hypothesize that participants will be more accurate for the object whose form is congruent with its motion. We also test amount of motion exposure. We know from past studies that longer motion exposures should lead to higher sensitivity. We additionally hypothesize that the benefit for object type should be especially pronounced in lower motion exposure conditions, since subjects have only the form of the object to rely on.

In Experiment 1, we manipulate object type, prime duration, and offset value, using an early/late judgment task. Object type was a human hand or an oval. We hypothesized that people would be more sensitive for the human hand than oval, since they perform motor simulation for the human hand but possibly not for the oval. We also hypothesized that people would be more sensitive for longer prime motion durations due to a simple evidence accumulation mechanism. We also predicted that there would be an interaction between the two factors, such that the advantage for the human hand would be more beneficial when people have less evidence about the motion (i.e., at shorter prime durations).

In Experiment 2, we also manipulate object type, prime duration, and offset value, but with a few changes. Instead of a human hand or an oval, we use a human hand or a robot hand. In contrast to a simple object like an oval, people do have expectations about how robots move, and they are different than the expectations people have for human hands (i.e., people expect robots to move with nonbiological motion and we always use biological motion). It is possible that we might see a larger effect of object type if people bring their expectations about objects to the task. We also used a different task: instead of responding “early" or “late" subjects responded whether or not the reappearance of the object was congruent. Then, we used signal detection accuracy measures to compute sensitivity and response bias to determine at what level of perception object type and prime motion duration affect predictions. We had similar hypotheses as in Experiment 1: there should be an accuracy benefit for the human hand over the robot hand, and for longer prime durations over shorter prime durations, and the object type advantage should be larger at the shorter prime duration than the longer prime duration. However, it is possible that there are effects



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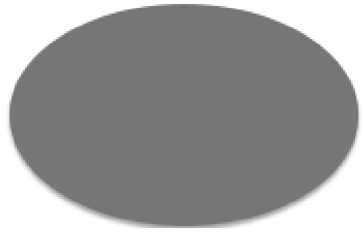


(b)

Figure 1: Stimuli from Experiment 1.

at different levels that could be driving these effects. For example, sensitivity (which we measure using d-prime) is thought to underlie lower-level perceptual processes, while response bias (which we measure using criterion) is thought to underlie higher-level decision processes.

2 Experiment 1

2.1 Methods

2.1.1 Participants

8 students from University of California, San Diego participated for course credit or as volunteers.

2.1.2 Materials

For the human hand stimulus, we used a frame from a video of a natural grasping motion recorded in our lab for a previous experiment. For the oval stimulus, we generated an oval and colored it the average color of the human hand stimulus. See Figure 1 for pictures of the stimuli.

2.1.3 Design & Procedure

We manipulated 3 factors: prime motion duration, object type, and offset value. Prime motion duration could be 100ms, 500ms, or 1000ms. We used these values because 100ms and 1000ms should be on the extremes of difficult and easy, and interesting effects might emerge in the 500ms prime duration since the trials are not too difficult and not too easy.

Object type was a human hand or an oval. We reasoned that people have an expectation that human hands move with biological motion, but have no expectations for the simple grey oval object. There is evidence that monkey mirror neurons fire to actions performed by human hands but not movements of simple objects (citation).

We used offset values of -350, -100, -50, 0, 50, 100, and 350 ms. We chose a large range of offset values so that we could fit robust psychophysical curves. Furthermore, there is evidence that these offset values are sufficient to produce psychophysical curves in this paradigm (see Parkinson et al., 2012 for more details).

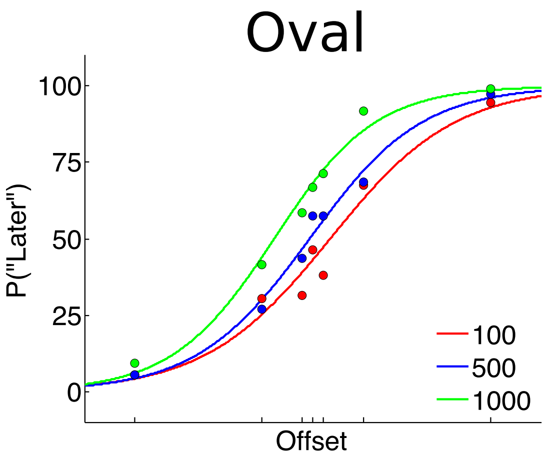
Participants' task was to respond "early" or "late". Participants were instructed to imagine during the occlusion that the object was moving in the same way they saw during the prime motion. They were told to respond "early" if after the occlusion the object reappeared at a point it should have already passed through, and to respond "late" if the object reappeared at a point it should not have gone through yet.

Trials were blocked by prime motion duration and object type, but not offset value. Each unique combination of prime duration and object type was presented in one block, making for a total of 4 blocks in the experiment. For example, a block might contain all trials with the human hand and 1000ms. We chose to include equal numbers of all offset types because of the nature of the task. If we presented equal numbers of congruent and incongruent trials, there would be many more congruent trials than for all other offset types, and furthermore, participants did not have a way to respond "congruent" using this task so it might have been confusing.

Stimulus display scripts and functions were written using the Psychophysics Toolbox for MATLAB (Brainard, 1997).

2.1.4 Data Analysis

We fit and compared sigmoidal psychometric curves using the `psignfit` toolbox for MATLAB (Fründ, Haenel, & Wichmann, 2011). In order to compare the curves for different conditions, we



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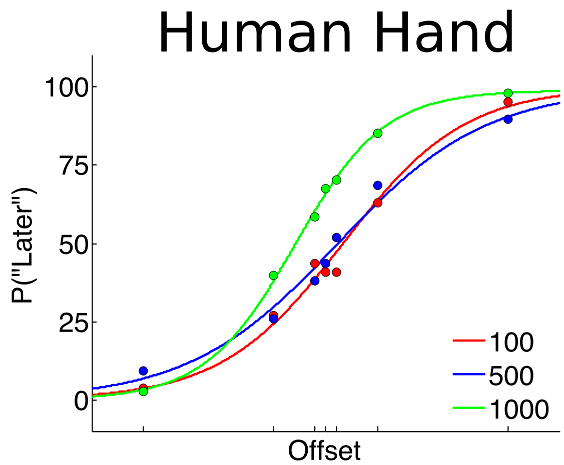

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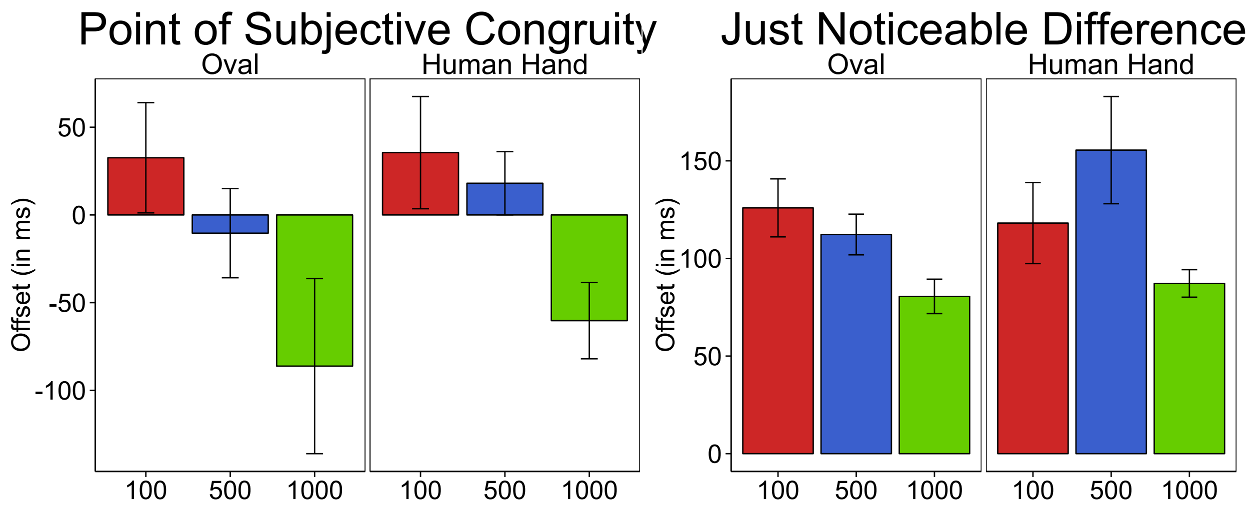
Figure 2: Psychophysical curves from Experiment 1.

used a Monte Carlo resampling procedure and bootstrapping[1] (see Wichmann & Hill, 2001a and Wichmann & Hill, 2001b for more detail on Monte Carlo resampling methods in psychophysics). In addition to directly comparing group-level curves, we also computed Point of Subjective Congruity (PSC) and Just Noticeable Difference (JND) on a subject-by-subject basis from single-subject curves. PSC was computed as the 50% point on the curve, i.e., the point at which subjects are responding 50% “early" and 50% “late", suggesting that that is the offset point they perceive as being congruent. JND is computed as half of the difference between the 25% and 50% point. It is taken as an index of how sensitive participants are to small differences in the offset values, since it roughly approximates the slope of the curve.

One additional important note is that for the psychophysical curves, we compared group-level curves, while for PSC and JND we extracted them from the individual subject curves and then compared them with ANOVA. So while PSC is roughly equivalent to the curve threshold and JND roughly corresponds to the slope curves, they might have different values since we extract them in different ways.

[1]I’d like to thank Luke Miller for assistance in computing and comparing the psychophysical curves.



(a)

(b)

Figure 3: Point of Subjective Congruity (PSC) and Just Noticeable Difference (JND) from Experiment 1.

2.2 Results

2.2.1 Psychophysical Curves

We found a significant difference between the 100 and 1000ms psychophysical curves for both oval and hand for both the full curves (oval: p=0.016; hand: p=0.032) and the threshold values (oval: p<0.001; hand: p=0.02). Within the hand object, there was an additional difference between 500ms and 1000ms prime motion duration for the full curve. There were no differences between the psychophysical curves for oval and hand in any prime motion condition. See Figure 2 for the group-level curves within the object types.

2.2.2 PSC and JND

We also compared the Point of Subjective Congruity (PSC) and Just Noticeable Difference (JND) between conditions. An ANOVA revealed a main effect of prime motion duration in PSC (p=0.005). Further comparisons revealed that there was a difference in PSC between the 100ms and 1000ms prime duration such that PSC was lower for 1000ms (p=0.004), between 500ms and 1000ms such that 1000ms was lower (p=0.02), but not between 100ms and 500ms (p=0.2). We did further pairwise comparisons within each object type and found the same pattern within the human hand (100 vs. 1000: p=0.036; 500 vs. 1000: p=0.02; 100 vs. 500: p=0.6). However, PSC was not significantly different between any of the prime durations within the oval object, except for a marginally significant difference between 100ms and 1000ms (p=0.07). See Figure 3a for PSC values in each condition.

We also found a main effect in JND of prime motion duration (p=0.013). Further pairwise comparisons revealed that there was a difference in JND between 100ms and 1000ms such that JND for 1000ms was lower (p=0.012) and between 500ms and 1000ms such that 1000 ms was lower (p=0.009), but not between 100ms and 500ms (p=0.5). Further pairwise comparisons within each object revealed that this pattern was identical in the oval object (100 vs. 1000: p=0.029; 500 vs. 1000: p=0.043; 100 vs. 500: p=0.47). However, there were no differences in JND between any prime durations in the human hand, other than a marginally significant difference between 500ms and 1000ms prime duration (p=0.055). See Figure 3b for JND values in each condition.

Although we found different effects of prime duration on PSC in each object type, there was no significant interaction between the two factors in the omnibus ANOVA (p=0.9), and there was also no main effect of object type (p=0.46). The same was true for JND as well (main effect: p=0.3; interaction: p=0.29).

2.2.3 Discussion

We found that there were no differences between the full curves, PSC, and JND between the two object types. We found that sensitivity (as measured by JND and curve slopes) increased as prime motion duration increased, and we also interestingly found that the offset at which participants perceived the object reappearance to be congruent became more negative at longer prime motion durations. In general, occlusion paradigm experiments tend to find that PSC is slightly negative overall, suggesting a perceptual ‘lag’ in the system (see Parkinson et al., 2012 for a longer discussion of this effect). Therefore, our PSC results seem to be consistent with this literature.

We speculate that because the non-human object was very simple (a gray oval), participants might not be using their expectations about how the objects should move since they have no expectations at all about the oval. Additionally, since the trials were blocked by object type, it is possible that participants had time to adjust to each object which might have washed out any true performance differences between the objects.

In Experiment 2, we use a non-human object that we know humans have explicit, non-biological motion predictions about: a robot hand. Additionally, we do not block trials by object type.

3 Experiment 2

3.1 Methods

The paradigm was identical to Experiment 1. Participants saw an object moving across the screen for a variable amount of time (prime motion), then the object was occluded for 500ms, and then the object reappeared and continued moving for 500ms. However, we changed four aspects of the design.

First, we only used prime motion durations of 110ms and 1000ms. We did not find any interesting differences between 500ms and the other prime durations in Experiment 1.

Second, instead of using a human hand vs. an oval as in Experiment 1, in Experiment 2 we use a human hand vs. a robot hand. We did this for two reasons. Firstly, the oval object in Experiment 1 was very simple. It is possible that participants were not using their high-level knowledge of the objects because they had no actual expectations about the simple oval. Secondly, on a perceptual level, a hand and an oval are very different objects and we wanted to make the two objects appear visually more similar.

Third, we changed the offset values we used. After doing some preliminary piloting with the new objects, we found that 20ms offset was too difficult for people to perform the task. So we switched them to 75ms and 200ms instead, making for a total range of offset values -350, -200, -75, 0, 75, 200, and 350ms.

Fourth, we changed the contrast of the objects and screen. Instead of using a white background and a black occluder, we used a gray background with a dark gray occluder. The robot hand stimulus we used it close to a white color, so we wanted participants to be able to distinguish it from the background of the screen. We changed the occluder color because we wanted to make the study a bit more ecologically valid. In real life, occluders do not suddenly appear; instead, object tend to move smoothly behind an object that is already visible. We reasoned that having an occluder that matched the color of the background a bit more would make the occlusion look a little more realistic.

Finally, we changed the task for this experiment. Instead of responding “early" or “late" after each trial, subject responded whether or not the object made a correct continuation. We did this so that we could compute more fine-grained measures of performance than in Experiment 1. We analyze the data in terms of a signal detection framework in order to determine both response bias and sensitivity.

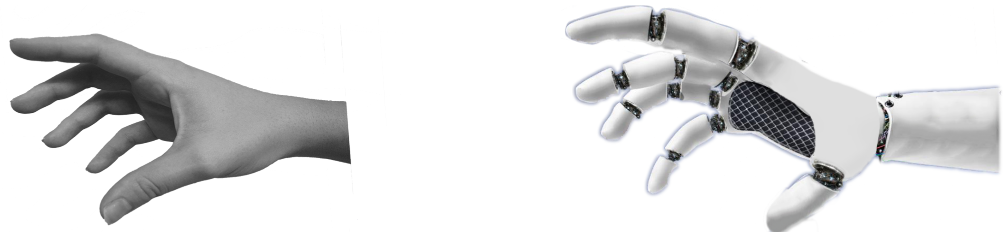
Trials were blocked by prime duration and offset type, such that each block had half of the trials congruent (i.e., 0 ms offset) and half of the trials one type of incongruent offset (e.g., 350ms). This was so that we could directly compute signal detection theory measures for each of the nonzero offset values and then aggregate across different conditions to compare. Trials were not blocked by object type.

3.1.1 Participants

13 students from UC San Diego participated in the experiment for course credit. We removed 4 participants from analyses for being under 50% accuracy for all the trials in the experiment, for a total of 9 participants whose data we analyzed.

3.1.2 Data Analysis

We performed four kinds of analyses for Experiment 2. First, we looked at accuracy. However, it is impossible to tell whether differences in accuracy are due to differences in sensitivity or response



(a) (b)

Figure 4: Stimuli from Experiment 2.

bias. So we also computed the signal detection measures d-prime (sensitivity) and criterion (response bias) (see Stanislaw & Todorov, 1999 for more information about these measures). Finally, we also analyzed reaction time on trials.

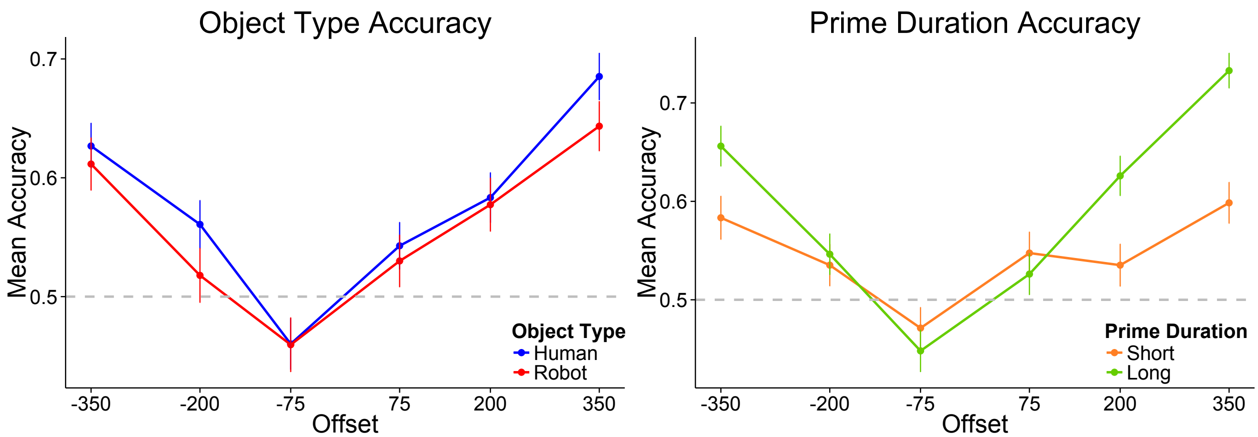
We divided the responses into four different types: hit, miss, false alarm, and correct rejection. If the trial is a true congruent trial, then the subject responding “yes" corresponds to a hit and a response of “no" corresponds to a miss. If the trial is an incongruent trial, then the subjects responding “yes" corresponds to a false alarm and the subject responding “no" corresponds to a correct rejection.

To calculate the sensitivity measure d-prime, we used the following formula:

$$d' = Z(H) - Z(F) \tag{1}$$

where H corresponds to the hit rate and F corresponds to the false alarm rate. Z is a function that maps values between 0 and 1 to a z-score relative to the normal distribution. However, there is a problem with values of 0 and 1: the z-score for 0 is $-\infty$ and ∞ for 1. There are a variety of different ways to avoid getting infinity values for d-prime. The one we adopt here is to calculate hit rate and false alarm rate slightly differently, by adding 0.5 to the numerator and 1 to the denominator:

$$H = \frac{\text{hits} + 0.5}{\text{hits} + \text{misses} + 1} \tag{2}$$



(a) (b)

Figure 5: Main effects of (a) object type and (b) prime duration in accuracy (object type difference is marginal). Dashed lines represent chance level accuracy.

$$F = \frac{\text{false alarms} + 0.5}{\text{false alarms} + \text{correct rejections} + 1} \tag{3}$$

This is known as a log-linear approach. For more information on other methods of counteracting undefined values in signal detection measures, see Stanislaw and Todorov (1999).

Calculation of our response bias measure, criterion, was done as follows:

$$c = Z(H) + Z(F) \tag{4}$$

For the accuracy data, we used logistic mixed-effects models since accuracy is a binomially distributed variable and thus ANOVA is inappropriate (for more information, see Jaeger, 2008). For d-prime and c, we used ANOVA since these are continuous measures (although there is still some debate about what analysis technique is most appropriate for signal detection measures, since they are ultimately derived from binomially distributed variables).

3.2 Results

3.2.1 Accuracy

We fit a logistic mixed-effects model using the package `lme4` for R (Bates, Maechler, Bolker, & Walker, 2014).[2] The intercept was significant, suggesting that overall participants were above chance ($p<0.0001$). We found a main effect of prime duration ($p<0.001$), such that participants were more accurate at the long duration than the short duration. We also found a main effect of offset ($p<0.0001$), such that participants were more accurate for offsets farther away from 0. We found an interaction between prime duration and offset ($p<0.001$). We found a marginal main effect of object type, such that participants were marginally more accurate for the human than the robot hand ($p=0.09$). We found no other main effects or interactions in the accuracy data.

We did further 2x2 interactions between prime duration and all the offset values to further understand the relationship between them. These interactions revealed that participants were more accurate for the longer prime duration at the 200ms, 350ms, and -350ms offsets ($p<0.001$), while they were less accurate for the longer prime duration at -75ms offset ($p<0.002$).

We did further pairwise comparisons for each of the offset values to further understand the main effect of offset. These revealed that participants were more accurate for -350ms offset than for -200ms and -75ms (p's<0.001), and marginally more accurate than 75ms ($p=0.06$). Participants were more accurate for the 350ms offset than for all other offsets (p's<0.03). Participants were more accurate for the 200ms offset than 75ms and -75ms (p's<0.05), and marginally more accurate than for the 200ms offset ($p=0.06$). Participants were less accurate for the -75ms offset than all other offset values (p's<0.0001). Participants were less accurate for the 75ms offset than for the 200ms, 350ms, and -350ms offsets (p's<0.05), but were more accurate than for the -75ms offset ($p<0.001$).

Discussion

We found that participants were more accurate for the longer prime duration than the shorter

[2]Full model specification: `Accuracy ~Object Type x Prime Duration x Offset + (1 | Subject)`. We included only random intercepts for subjects and not random slopes because we had problems with model convergence since our factors had many levels.

Predictor	F value	p value
Object Type	1.031	0.311
Block Offset	7.819	0.00000102 ***
Prime Duration	4.231	0.041 *
Object Type x Block Offset	0.100	0.992
Object Type x Prime Duration	0.169	0.681
Prime Duration x Block Offset	1.913	0.094
Object Type x Prime Duration x Block Offset	0.163	0.976

Table 1: D-prime ANOVA.

prime duration. We also found that participants were more accurate for offset values farther away from the true congruent offset. However, as noted above, accuracy data does not account for sensitivity and response bias which are separable measures. In the following section, we present analyses for d-prime (sensitivity) and c (response bias).

3.2.2 D-Prime

An omnibus ANOVA revealed a main effect of offset ($p<0.0001$), such that participants showed more sensitivity for offsets farther away from zero. We also found a main effect of prime duration, such that participants were more sensitive for the longer prime duration than the shorter prime duration ($p=0.041$). Finally, there was also a marginal interaction between offset and prime duration, such that people were more sensitive for the longer prime duration at the most extreme offsets ($p=0.094$). We found no other main effects or interactions in d-prime.

3.2.3 Response Bias (c)

An omnibus ANOVA revealed a main effect of object type, such that participants were more biased to respond “congruent" to the human than the robot hand ($p<0.0001$). There was also a strong main effect of prime motion duration such that participants were more biased to respond “congruent" to

Predictor	**F value**	**p value**
Object Type	21.813	0.00000564 ***
Block Offset	5.938	0.0000395 ***
Prime Duration	4.060	0.0453 *
Object Type x Block Offset	0.630	0.6770
Object Type x Prime Duration	0.021	0.8839
Prime Duration x Block Offset	0.678	0.6406
Object Type x Prime Duration x Block Offset	0.350	0.8815

Table 2: Criterion ANOVA.

1000ms prime duration ($p<0.045$). Finally, there was a main effect of offset with offsets closer to 0 biased to “congruent" responses ($p<0.0001$). We found no other main effects or interactions in response bias.

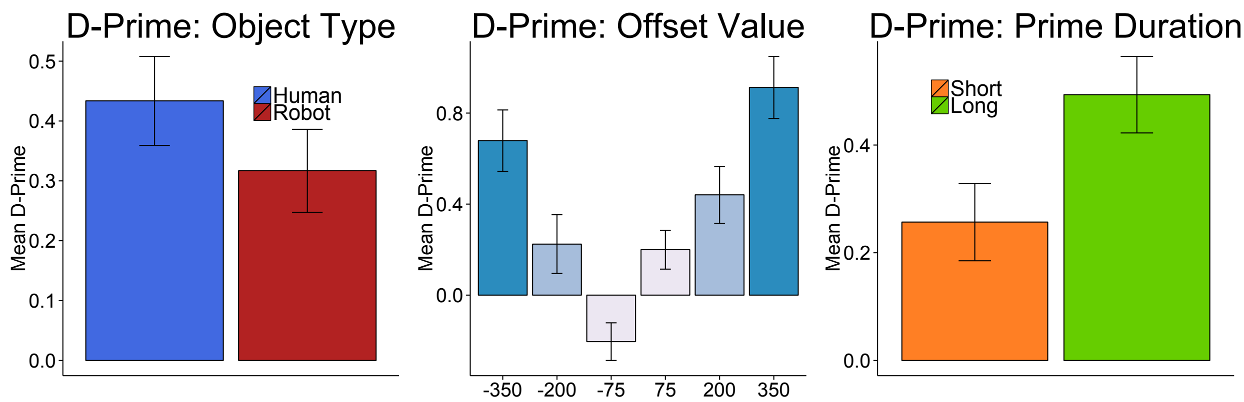
3.2.4 Reaction Time

An omnibus ANOVA revealed a main effect of prime duration in the reaction time data, such that participants were faster to respond at the shorter prime duration than the longer prime duration ($p<0.001$). We also found a marginal main effect of offset, such that participants were faster to respond to offsets closer to 0 ($p=0.08$).

3.2.5 Discussion

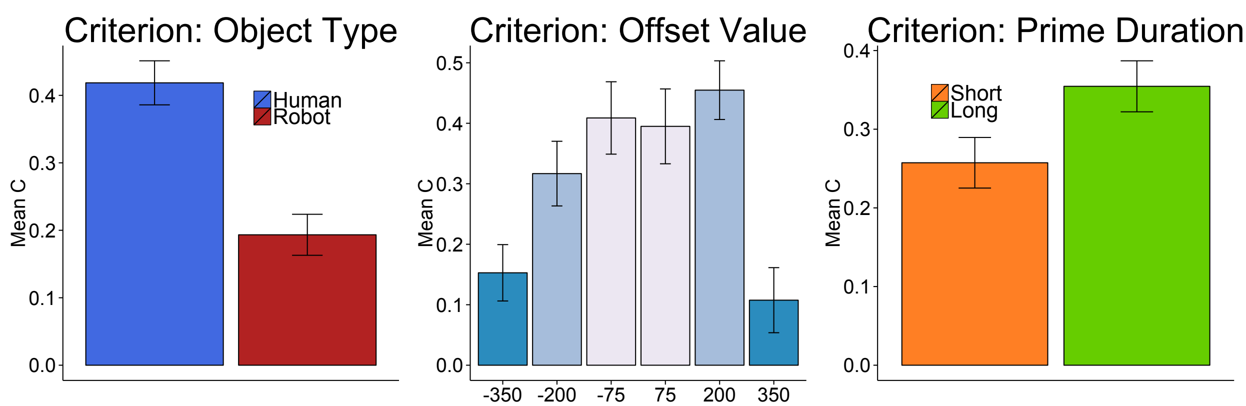
Interestingly, in reaction time we found that subjects responded faster on the trials for which they were the least accurate and sensitive. We think that this might be due to guessing behavior. If participants are not able to make accurate judgments, they might simply be guessing and just responding quickly.

The d-prime and c analyses revealed that object type and prime duration affect participant’s behavior in different ways. Prime duration had a large effect on both sensitivity and response



(a) (b) (c)

Figure 6: D-prime main effects in Experiment 2. There was a main effect of prime duration and offset, but no main effect of object type.



(a) (b) (c)

Figure 7: C (response bias) main effects in Experiment 2. There were significant main effects of object type, prime duration, and offset.

bias, suggesting that prime duration affects both participants' perceptual abilities to distinguish congruent from incongruent offsets. However, we only found a difference between object type in response bias and not in d-prime.

Finally, it is worth noting our d-prime results in offset values. We found an asymmetry between early and late offsets, such that d-prime was in general lower for early offsets than later offsets. In fact, d-prime was even negative at the -75 offset value. However, this makes sense in the context of Experiment 1; PSE values for the 1000ms prime duration were around -75 for both the human and dot objects. This suggests that people were perceiving -75 offset as the congruent offset, which

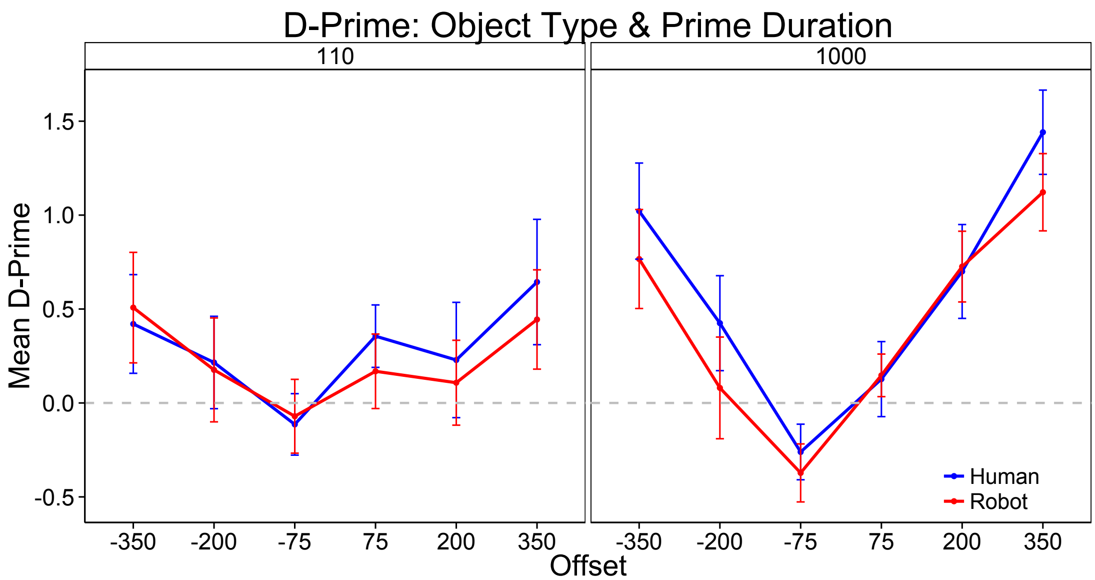


Figure 8: Mean d-prime by offset. The top panel is the short (110ms) prime duration, and the bottom panel is the long (1000ms) prime duration.

accounts for the low d-prime.

4 General Discussion & Future Work

In both experiments, we found no effect of object form on our sensitivity measures, but we did find a difference of prime motion duration. In Experiment 2 when we measured both sensitivity and response bias, we did find a response bias difference between the two different object types. This suggests to us that the difference between the object forms occurs not on a low-level perceptual level, but rather on a later-stage decision process involved in actually making the response. We hypothesize that this difference is due to the appearance of naturalness of the two objects. A human hand moving with biological motion appears very natural, while a robot hand moving with biological motion appears very unnatural. It is possible that since the human hand is much more natural, they were more lenient in their judgments of the human hand and were more likely to respond “congruent" since overall it appears more natural than the robot hand. Conversely, prime motion duration affects both the low-level perceptual processes involved in sensitivity and the higher-level decision processes. These factors did not interact, suggesting to us that object form and amount of motion exposure affect the prediction process separately.

Although these results are intriguing, there are a couple of problems with this experiment. Firstly, the 110ms prime duration trials were too difficult for subjects to do in the beginning of the experiment, so blocks of 110ms prime motion duration always occurred later in the experiment. Therefore, our results for prime motion duration might be due to unpredictable fatigue or practice effects. It is possible that we saw a difference in response bias between the two prime durations because subjects got used to the task and started to subconsciously balance their responses more, since we observed a lower response bias in the short prime motion duration condition. Furthermore, it is possible that subjects were fatigued, causing them to become less sensitive over time, affecting their d-prime negatively. Another possibility is that subjects got better as they practiced, leading to a higher d-prime than we would have observed if they saw the trials earlier. Therefore, in future experiments we plan to increase the short prime duration to be slightly longer (possibly 500ms) so that subjects are able to do the task right away and we do not have to always present the short prime duration blocks later in the experiment.

Another potential problem with this experiment is that the task was extremely difficult for participants. If the task is too hard for participants, it might be pushing any possible effects down to floor so that we cannot see what factors are truly playing a role and which ones are not. In the 110ms prime duration condition, mean accuracy was just barely above chance in most of the conditions. In future experiments, it would be useful to make the task easier. Another further point of interest is that participants in Experiment 1 were actually more accurate than participants in Experiment 2. There are multiple possible reasons for this, but for us it seems the most likely explanations are the nature of the task and the contrast of the screen. In Experiment 1, participants' task was to respond whether the object reappeared at a point too early or too late along the motion trajectory. It might be possible that this task is easier than deciding whether or not the continuation was congruent. Also, in Experiment 2 we changed the contrast of the screen so that the stimuli were grey on a grey background with a grey occluder box. We did this because or robot hand stimulus was almost white, and would have been difficult to see on a white background. In future experiments, we plan to change the robot hand stimulus so that it is equally visible as the human hand so that we can change the background to white and get a higher contrast.

Apart from fixing the problems in the current experiment, we have some ideas for future extensions of this research. We are particularly interested in looking at stimuli that show more goal-directed actions. Our stimuli in this experiment were simply static images that moved along a predefined arc trajectory. It would be interesting to show more naturalistic actions that require participants to simulate more in depth. For example, showing a hand making a grasping action would be very interesting. Grasping requires a lot of fine-grained motor coordination, and it would be interesting to see whether differences emerge in perception or prediction between a human hand and a non-human hand performing the same complex action, since this more directly engages motor simulation resources.

5 Conclusions

We found that both object form and amount of motion exposure contribute to how people make predictions about moving objects, but that these factors affect prediction differently. Firstly, we found that overall participants were more biased to respond that a continuation was congruent for the human hand than for the robot hand. For motion exposure, we found that when participants had a longer time to view the motion before it was occluded, they were more sensitive. This suggests that while amount of motion exposure affects both low-level perceptual processes and high-level decision processes, object type only affects high-level decision processes. Additionally, object form and motion exposure did not interact, suggesting that they are two separate processes during action prediction.

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