Can humans learn to deviate from the constant bearing angle strategy?

An investigation into human ball-catching behavior under visual uncertainty in a virtual reality environment

Bachelor-Thesis von Dominik Straub
Tag der Einreichung:

1. Gutachten: Constantin Rothkopf
2. Gutachten: David Hoppe

TECHNISCHE UNIVERSITÄT DARMSTADT

Institute of Psychology
Psychology of Information Processing

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Darmstadt, den 07. März 2017

(Dominik Straub)

Abstract

The question how humans run to intercept balls has been addressed in a multitude of studies. There are two conflicting views on this topic. Proponents of a model-based view argue that humans employ an internal model of the environment, which they use to predict the trajectory of the ball and plan actions in an optimal way according to these predictions. By contrast, most of the work on catching balls has relied on different reactive heuristics as an explanation, which establish a direct relationship between robust optical variables and behavior. For example, the constant bearing angle (CBA) theory states that humans null the rate of change of the target's horizontal angle w.r.t. an allocentric reference direction. We tested in a within-subjects study (n = 14) whether humans can learn to deviate from the CBA strategy when catching balls that move at a constant velocity. The contrast of the balls was varied over time in two different ways, such that they were hard to see when subjects walked according to the CBA strategy. Our results do not indicate that humans deviate from CBA under these conditions. However, the fact that subjects managed to catch the balls when continuous vision of the ball trajectory was not available offers some insights about the role of prediction in catching balls. Based on this, we suggest that additional research is needed to investigate how actions are guided when visual information is lacking.

Zusammenfassung

Die Frage, wie Menschen laufen, um Bälle zu fangen, war bereits Gegenstand vieler Studien. Es gibt dazu zwei widersprüchliche Sichtweisen. Anhänger von modell-basierten Theorien behaupten, dass Menschen über ein internes Modell ihrer Umgebung verfügen, mit welchem sie die Flugbahn des Balles vorhersagen und davon ausgehend optimale Aktionen planen. Im Gegensatz dazu haben sich die meisten Arbeiten zum Thema Bälle fangen auf verschiedene reaktive Heuristiken als Erklärung verlassen, die eine direkte Beziehung zwischen robusten optischen Variablen und dem Verhalten herstellen. Die Constant-Bearing-Angle-Theorie (CBA) zum Beispiel besagt, dass Menschen die Änderungsrate des horizontalen Winkels ihres Ziels in Bezug auf einen allozentrischen Referenzrahmen null halten. Wir haben in einer Within-Subjects-Studie (n = 14) getestet, ob Menschen lernen können von der CBA-Strategie abzuweichen, während sie Bälle fangen, die sich mit einer konstanten Geschwindigkeit bewegen. Der Kontrast der Bälle über die Zeit wurde auf zwei verschiedene Arten so variiert, dass sie schwer zu sehen waren, wenn sich die Versuchspersonen gemäß der CBA-Strategie bewegten. Unsere Ergebnisse legen nicht nahe, dass Menschen unter diesen Bedingungen von CBA abweichen. Dass die Versuchspersonen jedoch in der Lage waren, die Bälle zu fangen, auch wenn der Ball nicht durchgängig sichtbar war, bietet Einblicke in die Rolle von Vorhersagen beim Bälle fangen. Darauf aufbauend schlagen wir vor, dass weitere Forschung nötig ist, um zu klären, wie das Verhalten gesteuert wird, wenn visuelle Informationen nicht verfügbar sind.

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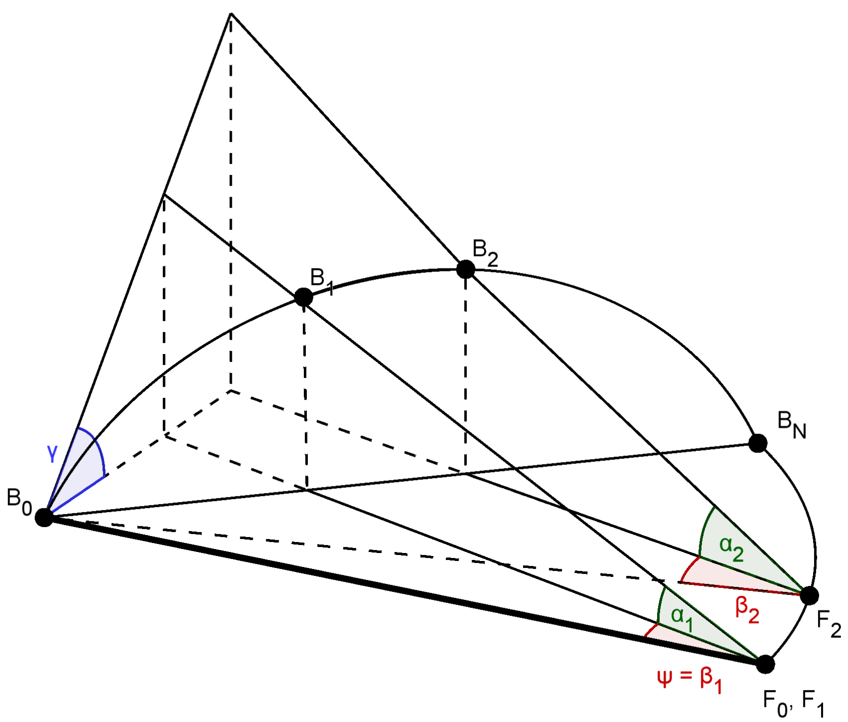
1 Introduction

How do humans navigate to intercept moving objects? For example, how does a baseball outfielder know where to run in order to successfully catch a fly ball? These questions - how humans accomplish interception tasks in general as well as the outfielder problem specifically - have been discussed in cognitive science for many years. Although catching balls might seem like a trivial problem since humans are so incredibly good at it, the computations required to solve it are exceedingly difficult due to perceptual uncertainties and delays in motor response. These perceptual uncertainties are rooted for example in ambiguities about distance and size of the ball (e.g. Battaglia, Kersten, & Schrater, 2011) and in noisy measurements of stimulus speed (e.g. Stocker & Simoncelli, 2006). There have been two general approaches to explaining human behavior in ball-catching: theories based on heuristics and theories based on internal models. First, an overview over the heuristics used to explain behavior in interception tasks is presented, followed by experimental studies that aimed to verify these heuristics. Second, recent work that indicates that internal models could play a role is discussed, leading to the question whether humans can learn to deviate from known heuristics.

1.1 Heuristics in ball catching

Most of the work published on ball-catching has focused on heuristics based on robust optical variables that are used to guide interception of the ball on-line. According to these heuristics, currently available visual information is sufficient to control the catcher's actions and thus early estimates do not need to be integrated when new observations are made. This is in accordance with Marewski, Gaissmaier, and Gigerenzer's (2010) view on human rationality, who argue that complex internal models that predict the physics of the world are not needed in order to successfully catch balls. Instead, humans supposedly employ a heuristic that simply keeps the angle of gaze constant while fixating the ball.

Figure 1: An illustration of the outfielder problem.

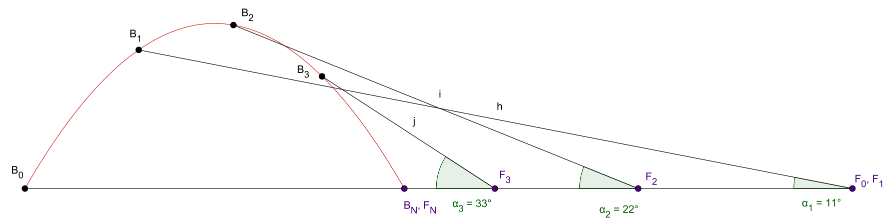


This idea dates back to work by Chapman (1968), who first introduced the theory known as Optical Acceleration Cancellation (OAC). He considered the case of baseballs coming directly towards the fielder (the terms fielder and player are used interchangeably in this thesis) and proposed a principle for how the fielder should move in the vertical plane defined by the trajectory of the ball (the ball's flight plane): Maintaining a constant rate of increase in the tangent of the elevation angle α (see Fig. 1) - i.e. nulling the acceleration of $tan\alpha$ - leads to a successful interception of the ball. In the case of a home run (when the ball lands behind the fielder), $\frac{d\tan\alpha}{dt}$ increases. If the fielder runs too far out (e.g. in the case of a so-called pop-up to the infield), $\frac{d\tan\alpha}{dt}$ decreases. OAC can be achieved by controlling one's movement, such that

$$\frac{d\tan\alpha}{dt} = const \tag{1}$$

at any time until the ball is caught (see Fig. 2).

Figure 2: The Optical Acceleration Cancellation strategy of catching balls hit directly at the fielder. The time steps {1,2,3} are evenly spaced. The player (indicated by the points F_n) controls their movements in a way such that the velocity of the elevation angle α remains constant over time.



OAC is a robust heuristic which works even for balls that do not follow a perfect parabolic trajectory since it directly couples the movements of player and ball. However, in a real game of baseball (or any game that involves balls) most balls are not thrown directly towards the player. So, obviously, there must be a mechanism that controls the player's lateral movement. For this, Chapman (1968) proposed a second heuristic: the constant bearing angle (CBA) strategy, which is based on the idea that a player maintains the bearing angle ψ (the angle of the ball away from an allocentric reference frame, also known as the azimuth angle; see Fig. 1) constant. A detailed illustration of the CBA strategy over time is depicted in Fig. 3.

While the OAC heuristic is simple and somewhat appealing, McBeath, Shaffer, and Kaiser (1995) point out a few important flaws. One point is that it is necessary to precisely discriminate accelerations in order to maintain a constant velocity of α, a task which humans are not very good at (Todd, 1981). Additionally, it is known that baseball players find balls coming directly towards them harder to catch than balls hit slightly to the side. This contradicts the idea that humans use one heuristic for vertical movements and an additional one for lateral movements, which would imply that balls for which only vertical movement is needed are easier to catch. Therefore, McBeath et al. (1995) argue that the two movement components are controlled jointly by maintaining the observed angle of the ball constant with respect to the background horizon. γ is the angle of the ball's image projected onto a two-dimensional surface (see Fig. 1). By keeping the optical trajectory projection angle γ constant, a player maintains a linear optical trajectory (LOT), which implies

$$\begin{aligned} \gamma &= const \\ \Rightarrow \tan\gamma &= const. \end{aligned} \tag{2}$$

Figure 3: The CBA heuristic at different timesteps, indicated by ball positions B and player positions F at different timesteps {0,1,2,3}. The bearing (or azimuth) angle ψ is the angle between the ball, the fielder and an allocentric reference direction (the dotted lines in this illustration). This angle remains constant over time, leading to a successful interception for both trajectories t_1 and t_2. One can see that the CBA strategy does not dictate a specific trajectory.

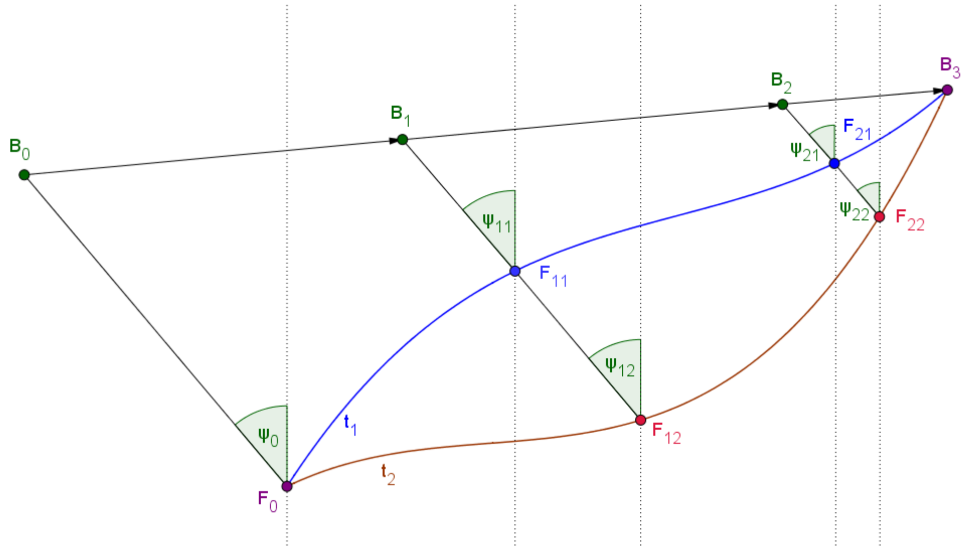
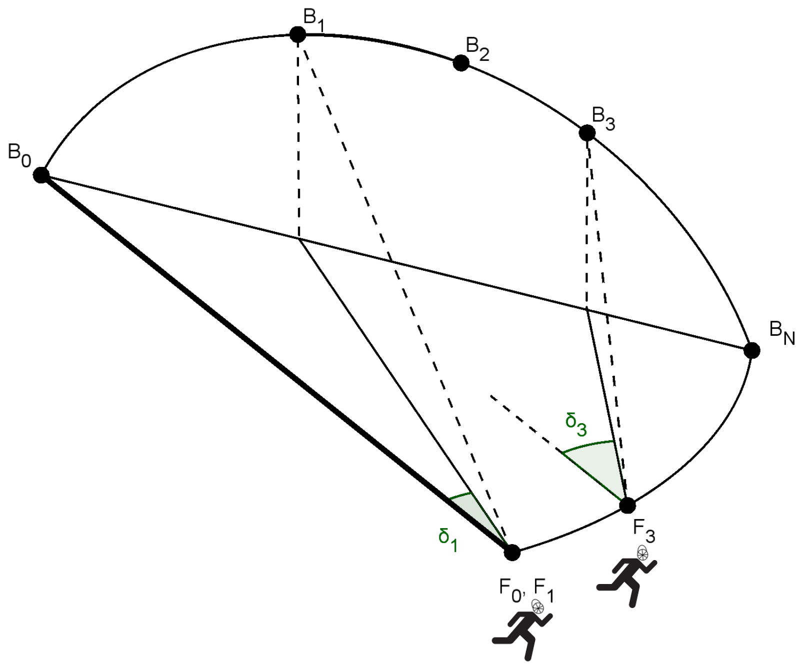


Figure 4: The GOAC theory of catching. δ is horizontal angle between the ball launch site, the fielder and the ball. F are fielder positions, while B indicate ball positions.



Note that it does not matter how exactly the horizontal optical angle β and the elevation angle α vary, as long as the ratio $\tan \gamma = \frac{\tan \alpha}{\tan \beta}$ is constant. Aboufadel (1996) showed mathematically that the LOT model leads to a successful interception, stressing however that his work does not provide proof of its correctness in the sense that the strategy is indeed used by humans.

Another possible heuristic for catching balls is the Generalized Optic Acceleration Cancellation (GOAC) theory (McLeod, Reed, & Dienes, 2006), which provides an alternative to CBA for the player's lateral movement component. The GOAC

model introduces the viewing direction of the fielder (see Fig. 4). The angle δ is defined as the horizontal angle between the initial direction from the player's position to the ball and the current direction from the player to the ball. Therefore, δ_t captures how much the player's view direction has rotated by time t (w.r.t. their initial viewing direction). It is important to note that this assumes that the fielder always fixates the ball. Consequently, δ is positive when the fielder is laterally behind the ball, and negative when the fielder is ahead of the ball. McLeod et al. (2006) argue that no specific strategy is needed in order for the player to achieve lateral alignment with the ball, as long as their mean lateral velocity is approximately equal to the ball's and δ does not accelerate during the latter part of the flight. Depending on the ball's flight duration, different strategies are possible: one could for example accelerate first to quickly reach the balls flight plane and then maintain lateral alignment with the ball (for slower balls) or accelerate at a constant rate and achieve lateral alignment with the ball only at the interception location (for faster balls).
To date, it is still up to debate which of the heuristics presented in this section are actually used by humans when catching balls. In the next section, several experimental approaches that tried to answer this question are discussed.

1.2 Experimental studies

Table 1 provides an overview over experimental studies on ball catching and locomotor interception in general. Before discussing some of the studies in detail, a few things should be noted. First, the experiments in the table can roughly be grouped into two categories: experiments with fly balls and experiments in which the target moves in a horizontal plane. Second, some experiments use real balls and record ball and subject positions with cameras or other position tracking systems, while others use virtual reality (VR) environments. A VR environment can be as simple as a visual scene presented on a screen and controlled with a steering wheel, or as sophisticated as a setup in which experimental subjects can walk around freely while wearing a head-mounted display. It is important to keep the limitations that come with different experimental setups in mind. For example, in experiments on screens, the direction of movement is often coupled with the viewing direction of the subject, which is obviously not the case in a naturalistic setting.

1.2.1 Fly balls

In one of the earliest studies about catching balls (McLeod & Dienes, 1993), the OAC strategy was put to a test by recording catches of balls aimed directly towards a fielder. McLeod and Dienes (1993) present plots that show the subject's mean velocity and their acceleration of the elevation angle α for 15 successful catches and conclude that humans accelerate until they reach a velocity that enables them to null $\frac{d^2\alpha}{dt^2}$, leading to a successful interception. In a similar study, McLeod and Dienes (1996) provide additional evidence for the OAC model, again using balls aimed directly at the fielder. Again, the subjects maintained $\frac{d^2\alpha}{dt^2} = 0$, even if they had enough time to run to the interception point before the arrival of the ball and wait there, which would imply a deviation from OAC. This is taken as evidence against predictive strategies, where a player computes the expected point of interception from observations of the initial conditions of the ball and then runs to that point.

McBeath et al. (1995) performed two experiments, for each of which 31 trials with real balls from 2 catchers were analyzed. In the first experiment, the fielder's running paths were recorded using cameras mounted above the field. The curvature of the running paths is interpreted as evidence against an OAC with CBA strategy, which would predict straight paths. For the second experiment, the catches were recorded from the fielder's point of view in order to examine the visual angles α and β. The relationship between $\tan\alpha$ and $\tan\beta$ could be well described by a linear function, indicating that the subjects maintained a LOT by nulling acceleration in $\tan\alpha$ and $\tan\beta$. The authors conclude from these results that the LOT model explains human ball catching behavior better than OAC with CBA for the lateral movement component. While the linearity of $\tan\alpha$ and $\tan\beta$ is indeed consistent with the LOT model, it might as well be the case that humans cancel out the acceleration in $\tan\alpha$ and employ a separate strategy for lateral movements, which could also lead to a linear optical trajectory without explicitly controlling β.

In a similar experiment, Mcleod, Reed, and Dienes (2001) (listed in Table 1 as McLeod et al. (2006), in which the data were reanalyzed) tested this idea by increasing the range of possible values for α and β. Like McBeath et al. (1995), they also observed curved paths and a significant linear term in the regression of $\tan\alpha$ on $\tan\beta$. However, they also reported a significant quadratic term in the regression model for most trials. Additionally, while $\tan\alpha$ increased linearly with time (as predicted by the OAC model) in almost all trials, $\tan\beta$ increased linearly in some but not all trials. These results confirm that humans cancel the optical acceleration of the elevation angle but suggest that LOT is not a general strategy for catching balls under different conditions. Based on this, the GOAC model of catching (McLeod et al., 2006) was developed (see Section 1.1), which was shown to fit the data from the previous experiment (Mcleod et al., 2001) well.

The first study on catching fly balls that used a VR environment presented via an HMD was done by Fink, Foo, and Warren (2009). They made 12 subjects catch virtual fly balls, which moved on a parabolic trajectory. The experiment took place in a large lab space, in which participants could walk around freely. In order to distinguish OAC, LOT and predictive strategies, they perturbed half of the balls at the moment they reached their apogee. After that, the balls descended on a linear trajectory with the same end point as the parabolic trajectory. Like in most previous studies, $\tan\alpha$ increased linearly with time (in accordance with the OAC model) for normal trials. For the perturbed trials, $\tan\alpha$ could be well described by two linear models, with the slope changing at the time of perturbation, indicating that subjects are able to adjust their movements in order to maintain OAC even when the ball's trajectory changes. However, the relationship between $\tan\alpha$ and $\tan\beta$ could not be well explained by a linear model for the perturbed trials. This suggests that the movement towards the ball (related to the change in $\tan\alpha$) and the lateral movement (related to the change in $\tan\beta$) are not coupled (contrary to the LOT model). For the lateral movement, the results presented were consistent with the CBA strategy, suggesting OAC with CBA as the correct model for catching balls. But could these results also be explained by a predictive strategy? Because catching performance was not significantly worse in perturbed trials and the rate of change in $\tan\alpha$ changed when the balls were perturbed, Fink et al. (2009) argue that humans do not use a strategy based on trajectory prediction (TP), which supposedly provides "no reason to expect the linear increase in $\tan\alpha$" (Fink et al., 2009, p. 6). This, however, is based on the assumption that predictive strategies only use information from the initial phase of a ball's trajectory and can not be adjusted when new observations are made. This is a greatly simplified understanding of predictive strategies since those might as well entail mechanisms that cope with new observations under uncertainty and update predictions based on those.

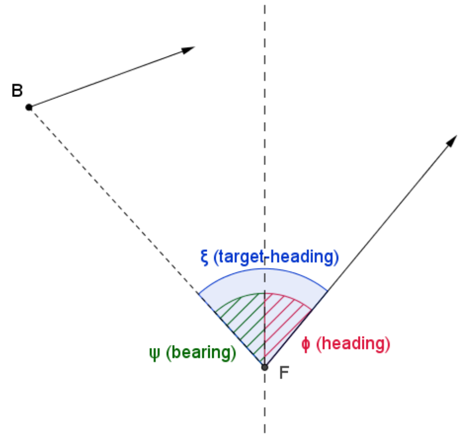
Taken together, the studies presented in this section still leave a lot of open questions. While empirical evidence seems to favor OAC with some strategy for lateral movement other than LOT, it is still not clear which is the correct model for lateral movements. It has also not been proven that the heuristics used to explain human behavior are indeed the mechanisms that humans use to guide their behavior and not just geometric relations that hold true, but can be explained by some more general strategy that perhaps includes an internal model of the world and the perceptual and motor uncertainties involved (more about this in Section 1.3).

1.2.2 Targets moving in a horizontal plane

For targets moving parallel to the xz-plane (the ground), the most prominent heuristic is the CBA strategy (see Fig. 3). Maintaining a constant bearing guarantees interception of a target that moves at a constant velocity in the xz-plane. The CBA strategy has therefore been discussed as the mechanism for avoiding collisions with moving obstacles (Cutting, Vishton, & Braren, 1995) and for intercepting moving targets (Lenoir, Musch, Thiery, & Savelsbergh, 2002; Lenoir et al., 1999). However, in the experiments conducted by Lenoir and colleagues, subjects moved on a linear trajectory with a bicycle and were only able to control their speed. In this setting, there is no difference between maintaining a CBA and a constant target-heading angle (CTHA, see Fig. 5), since the heading angle does not change. This was pointed out by Fajen and Warren (2004), who did a series of experiments in a VR environment, in which participants could walk freely, thereby removing the coupling of the target-heading and bearing angle. The data from these experiments were later reanalyzed and compared to paths produced by different models (Fajen & Warren, 2007). These models take the form of first-order differential equations that null some angle (or its rate of change). The best fit to the data was the CBA model, which nulls $\frac{d\psi}{dt}$, indicating that humans turn until they are able to maintain a constant bearing angle while walking on a straight path. In an experiment with subjects walking on a treadmill in front of a screen, Bastin, Craig, and Montagne (2006) provided additional support for the CBA strategy. The targets approached on a curvilinear path, while subjects walked at a fixed speed but controlled their velocity by changing their direction of movement.

The CBA model again provided the best fit to the data, explaining 56% of the total variance at the trial level and 74% at the group level (mean data across subjects and trials). Since targets in the real world often change their speed, Diaz, Phillips, and Fajen (2009) tested if the CBA strategy would hold for targets that changed their speed after a few seconds to a random speed drawn from a Gaussian distribution. A model that nulls the rate of change in the bearing angle at a future time $t + \Delta t$ provided a better fit to the data than the CBA model. This suggests that a purely reactive on-line control strategy like CBA might not be enough to explain human behavior when the target velocity is not constant and prediction of future target behavior might play a role. Another more recent study that casts doubt on a pure CBA model was performed by Bastin, Fajen, and Montagne (2010). Subjects sat in front of a screen and controlled their speed and direction using a gas pedal and a steering wheel. The results show that humans adjust their direction differently based on how close they are to their maximum speed, which indicates that the perception of whether or not it is possible to intercept a target at one's current speed plays a role. This is in contrast to the CBA strategy, which does not specify how exactly the adjustments of speed and direction are coordinated.

Figure 5: Definition of bearing, heading and target-heading angle used in this thesis. Angles clockwise from the z axis are positive, counter-clockwise angles are negative. F is the subject's position, B is the ball position. For both of these objects, the vector in the illustration indicates the direction of movement.



1.2.3 Catching heuristics in non-human animals

Some of the heuristics described above (or similar ones) have also been observed in non-human animals. For example, the CBA strategy has been observed in teleost fish (Lanchester & Mark, 1975) and dragonflies (Olberg, Worthington, & Venator, 2000) navigating towards their prey. Dogs have been shown to maintain a LOT when catching frisbees (Shaffer, Krauchunas, Eddy, & McBeath, 2004). Two dogs from different breeds were equipped with a video camera and had to catch frisbees thrown from different angles. They kept the rate of change in the elevation angle α constant (OAC) and also maintained a linear relationship between $\tan\alpha$ and $\tan\beta$ (as predicted by the LOT model). This result is especially interesting since the trajectories of frisbees are less predictable than the approximately parabolic trajectories of fly balls. A similar result has been found for echolocating bats (Ghose, Horiuchi, Krishnaprasad, & Moss, 2006), who approach their target using the constant absolute target direction strategy, which is similar to the CBA strategy but results in optimal paths even for unpredictable targets like insects.

Table 1: An overview over experimental studies on ball catching.

Publication	Target type	Type of experiment	Lab size, L (x W x H)	Target speed
McBeath et al. (1995)	fly balls	real balls	30 m x 10 m (read from Fig. 3)	N/A
McLeod and Dienes (1996)	fly balls	real balls	$\sim$ 50 m	20 - 25 m/s
Lenoir et al. (1999)	horizontal target	bicycle	$\sim$ 22 m	2.03 ± 0.04 m/s (fast) or 1.83 ± 0.04 m/s (slow)
Lenoir et al. (2002)	horizontal target	bycicle	$\sim$ 26.5 m	1.55 ± 0.03, 1.84 ± 0.04 and 2.63 ± 0.06 m/s
Fajen and Warren (2004)	horizontal target	VR (HMD)	12 m x 12 m	0.6 m/s
Shaffer et al. (2004)	frisbees (caught by dogs)	dogs	14 m (maximal distance moved by the dogs)	N/A
Ghose et al. (2006)	insects (caught by bats)	bats	7.3 m x 6.4 m x 2.5m	$\sim$ 1 - 4 m/s (read from Fig. 2 and 4)
McLeod et al. (2006)	fly balls	real balls	N/A	4.8 m/s (experiment 1) varying (experiment 2)
Sugar, McBeath, and Wang (2006)	balls rolled along the floor	real balls	10 m x 7 m	2 - 7 m/s
Diaz et al. (2009)	horizontal target	VR (screen)	N/A	$\sim$ 8 - 11 m/s; changed after 2.5 (drawn from Gaussian: m=15 m/s, sd=5 m/s)
Fink et al. (2009)	fly balls	VR (HMD)	12 m x 12 m	8.7 m/s (forward balls), 9.3 m/s (backward balls)
Bastin et al. (2010)	horizontal target	VR (screen)	N/A	3.21, 3.57, 3.93, 4.29, 4.64 m/s (slow), 4.5, 5, 5.5, 6, 6.5 m/s (medium) and 5.8, 6.4, 7.1, 7.7, 8.4 m/s (fast)
Wang, McBeath, and Sugar (2015)	fly balls	real balls	25 m x 16 m x 7 m	typically between 2 and 8 m/s

Table 1: An overview over experimental studies on ball catching (continued).

Publication	subject speed	number of subjects	Proposed heuristic
McBeath et al. (1995)	N/A	2 (in both experiments respectively)	LOT
McLeod and Dienes (1996)	up to 6 m/s (read from Fig. 3)	6	OAC
Lenoir et al. (1999)	$\sim$ 1.6 m/s	26	CBA
Lenoir et al. (2002)	1.88 to 2.13 m/s	10 (experiment 1), 8 (experiment 2)	CBA
Fajen and Warren (2004)	$\sim$ 1.29 m/s	8 (experiment 1 and 3), 9 (experiment 2 and 4)	CTHA/ CBA
Shaffer et al. (2004)	N/A	2 dogs	LOT with OAC
Ghose et al. (2006)	1 to 4 m/s (read from Fig. 2 and 4)	8 bats	constant absolute target direction (CATD)
McLeod et al. (2006)	1.23 m/s (lateral speed)	5	GOAC
Sugar et al. (2006)	N/A	3	LOT and OAC
Diaz et al. (2009)	0 to 14 m/s	12	CBA at future time $t + \Delta t$
Fink et al. (2009)	N/A	12	OAC (either GOAC or OAC + CBA)
Bastin et al. (2010)	1 to 5 m/s (slow condition) 1.4 to 7 m/s (medium condition), and 1.8 to 9 m/s (fast condition)	30	affordance-based control
Wang et al. (2015)	N/A	11	LOT or predictive strategy

1.3 Internal models

As we have seen in the last few sections, most of the work on catching balls and interception of moving objects in general has used heuristics to explain human behavior. These heuristics establish a direct relationship between variables like the elevation angle α or the bearing angle ψ and the behavior. This has also been called 'on-line control' since actions are guided on-line by currently available visual information only. Proponents of a model-based view, on the other hand, argue that humans form an internal model of the world, which they use to predict the physics of the environment, allowing to plan and execute actions in an optimal fashion. In the example of ball-catching, this would mean that people use their observations of the position and velocity of the ball and their own body to update their internal model of the state of the environment. This model is then used to predict future states of the environment and to guide movements to a position that will likely enable the actor to catch the ball. As more recent studies have shown (Bastin et al., 2010; Diaz et al., 2009), a pure on-line strategy might not be sufficient to explain behavior in interception tasks. Whereas research about the outfielder problem and locomotor interception has focused on on-line control heuristics, evidence for predictive internal models has been found in other areas of motor control. For example, in an experiment in which humans had to catch balls starting 1.6 m above their hand on earth and in 0 g (on a space shuttle mission), catching responses were initiated too early in 0 g (McIntyre, Zago, Berthoz, & Lacquaniti, 2001). This observation leads to the conclusion that humans use an internal model of gravity that predicts that objects moving downwards accelerate, even if this is not in accordance with on-line visual information in 0 g. Additional evidence for prediction in catching balls was brought forth by Hayhoe and colleagues. A study with balls thrown with a bounce has shown that humans catching a ball make predictive saccades to the anticipated bounce point before pursuing the ball with their gaze (Hayhoe, Mannie, Sullivan, & Gorgos, 2005). Another interesting observation from that study is that subjects were unable to pursue the ball when it was replaced with a more elastic ball without their knowledge, suggesting that an internal model of the ball's physics could be necessary for smooth tracking. Similar results were found by Land and McLeod (2000), who showed that cricket batsmen also make predictive saccades to the bounce location and do not need to track the ball for longer than 200 ms afterwards for a successful interception. Anticipatory saccades were also observed in a VR experiment, in which subjects hit balls that changed their elasticity with a racquet (Diaz, Cooper, Rothkopf, & Hayhoe, 2013). Subjects consistently made saccades to a location slightly above the bounce point. When the ball's elasticity was changed, they adjusted the location of their fixation after the bounce in order to maintain a constant time between the bounce and the ball's arrival at their fixation location. In contrast to the study by Land and McLeod (2000), the subjects were not particularly experienced with ball sports, which suggests that predictive saccades are important regardless of expertise.

The studies presented in this section indicate that predictive models could play a role in motor control tasks similar to the outfielder problem. The first attempt to provide such a computational model for the task of running to catch a fly ball was carried out by Belousov, Neumann, Rothkopf, and Peters (2016), who described the task in terms of a partially observable Markov decision process (POMDP) and devised an agent based on optimal control to solve it. The policies that result from this agent fit the predictions made by LOT, GOAC, and CBA under the conditions of (McLeod et al., 2006). However, under conditions that would render it impossible to always fixate the ball during interception (e.g. because the fielder would have to run backwards at a very high speed), the model predicts deviations from these heuristics, in accordance with qualitative observations of baseball players.

1.4 Aim of this study

If humans do indeed employ a predictive model and plan optimal actions according to that model, deviations from known heuristics should be expected if adhering to these heuristics would make catching the target impossible or very difficult. In the present study, our aim was to test whether humans can learn to deviate from the CBA heuristic when catching balls that move at a constant velocity parallel to the horizontal plane. We designed an experiment in a VR environment, that enables participants to walk freely while intercepting balls launched from two different positions. A VR setup makes it possible to vary the visual uncertainty about the ball's position by changing its contrast. A player acting according to a predictive model would be expected to deviate from the CBA strategy if the ball's contrast changed in a way that it would be almost impossible to see when maintaining a CBA. To test this idea, we varied the balls contrast as a function of the subject's behavior in two different ways. In one condition, the contrast was a function of the rate of change in the bearing angle ψ, making it harder to see the ball when a CBA was maintained. In the other condition, the ball was only perfectly visible when the subject walked on a specific path, which differed distinctly from the typical paths produced by the CBA strategy. The ball's visibility decreased with the distance to that path. There was also a control condition, in which the ball's contrast was constant. The work presented here is the first study in which the amount of visual uncertainty about the target's position in an interception task is varied (via its contrast) as a function of the catcher's movements. The questions this thesis tries to answer are whether humans can learn to successfully intercept their target in these conditions and if the modifications of ball contrast elicit deviations from the CBA strategy. If it can be shown that humans are able to catch balls without maintaining a constant bearing angle, this could contribute to the debate whether human actions are guided by a set of simple heuristics drawn from a toolbox or by complex computations that incorporate uncertainties about the state of the environment in a statistically optimal way.

2 Method

2.1 Participants

14 undergraduate students (8 of them male, 6 female) with normal or corrected to normal vision participated in the experiment. All of them were right handed. The subjects were naive to the purpose of the experiment and were not paid for their participation. Upon arrival at the lab, they signed an informed consent form and were given an instruction text in German (see Appendix A). After that, any questions about the hardware setup and the procedure of the experiment were answered. They were then equipped with the hardware described in the following section and were allowed to familiarize themselves with the virtual environment prior to the start of the experimental trials.

2.2 Apparatus

The experiment was conducted in a 7 m x 11 m lab space. Participants were able to move freely in this area, while their positions were tracked using 4 WorldViz PPT-X cameras. They wore a backpack that contained a notebook (Intel Core i7-6700, 16GB RAM, NVIDIA GeForce GTX980M) connected to an Oculus Rift DK2 HMD (94 degrees horizontal field of view, 960 x 1080 pixel resolution for each eye). One marker of the PPT system was attached to the HMD for position tracking. Participants wore a baseball glove on their dominant hand, which was equipped with another PPT marker and an InterSense Inertia Cube 4 (for position and orientation tracking). Data from the position tracking system were transmitted to the notebook via WLAN and were used to update positions of the participant's view point and glove at 60Hz.

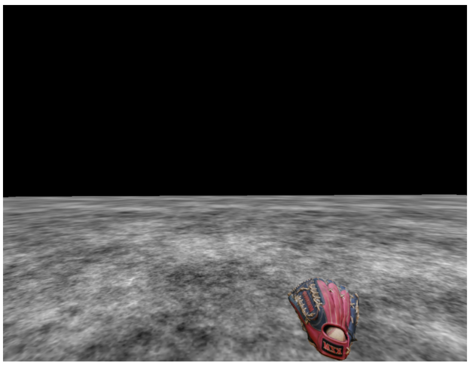
The participants' eye movements were recorded (also at 60Hz) with an eye tracker integrated into the Oculus Rift DK2 (SMI Eye Tracking HMD Upgrade). A 3-point calibration was performed prior to the start of the experiment.

The virtual environment was generated using WorldViz Vizard 5, a virtual reality software toolkit, which uses Python as a scripting language and comes with native support for all the hardware components described above.

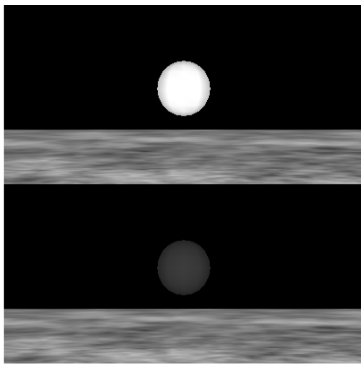
2.3 Visual scene

A typical view from a participant's perspective can be seen in Fig. 6. The texture on the ground is pink noise (Gaussian noised filtered in the frequency domain to obtain a frequency spectrum of the form $\frac{1}{f^{\alpha}}$, where $\alpha = 1.0000000000002$) and the background is black. Participants could see the movements of their dominant hand due to the baseball glove's position being updated with position data from the PPT. The balls to be caught in the experiment all had a radius of 0.15 m (see Fig. 6). The contrast of the balls was varied by changing their diffuse and ambient color values on a

Figure 6: The virtual environment as seen by a participant.



(a) The ground texture and baseball glove.



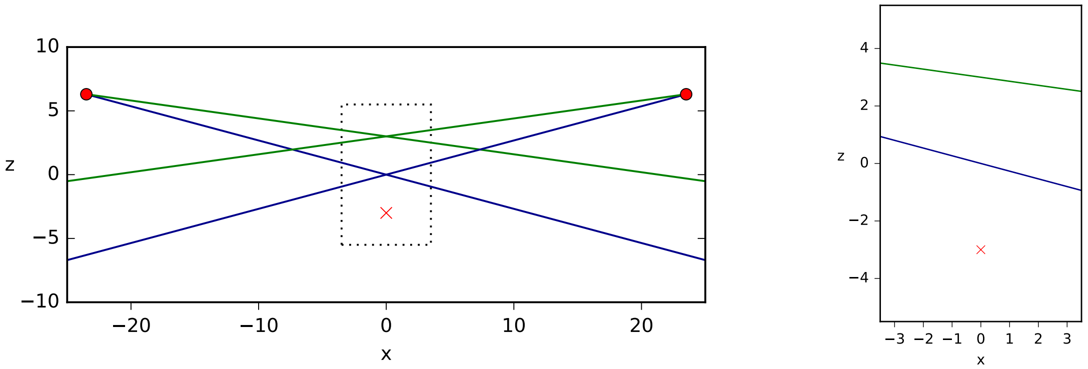
(b) The balls used in the experiment, one with a color value of 0.8, and one with a color value of 0.16

scale between black (RGB [0,0,0]) and white (RGB [1,1,1]). The exact functions that determined the contrast in the experimental conditions are described in Section 2.4. In the rest of this thesis, whenever ball contrast is mentioned we refer to the ambient and diffuse color of the ball.

2.4 Task

Participants were instructed to catch balls in the virtual environment with their baseball glove. Figure 7 shows a top view of the lab space. The balls started at one of 2 locations ([-23.5, 1.8, 6.3] or [23.5, 1.8, 6.3], indicated by the red circles) and moved at a constant velocity along one of two possible linear trajectories parallel to the xz-plane (blue and green lines, referred to as the *near/far* target conditions). At the beginning of each trial, a transparent blue pole (radius = 0.5 m, height = 1.4 m) and a green pole (radius = 0.25 m, height = 4 m) appeared in the virtual environment (see Fig. 8).

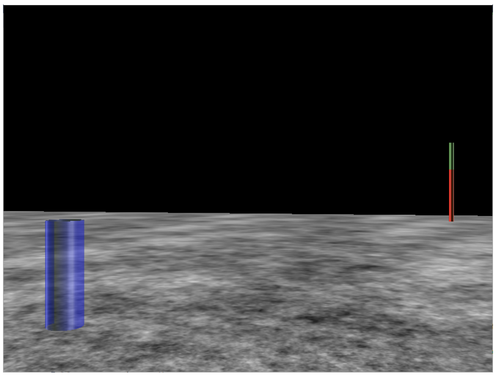
Figure 7: Top view of the virtual room: The area accessible to the participant is indicated by the dotted rectangle. Balls started at one of the two locations marked by red circles and moved along the blue or green trajectories. The blue and green trajectories are referred to as the *near* or *far* ball direction condition, respectively. The red cross indicates the participants' start location.



(a) The whole virtual room

(b) A closer view of the area accessible to the subjects (dotted rectangle in **(a)**)

Figure 8: The blue and green poles with which participants needed to interact in order to start a trial. The target pole started to turn red and a countdown sound started playing when participants faced it while standing in the blue pole. After 3 seconds (when the green target pole was completely red), the ball was launched.



The blue pole was always placed at [0, 0, -3] (red cross in Fig. 7) and the green pole's position was placed on the ground at the ball's initial location in the respective trial. In order to start the trial, participants had to stand inside the blue pole and face the green pole. If a subject's x and z positions were within the blue pole's radius and their view direction was equal to the direction of the green pole relative to their own position (with an error tolerance of 5 degrees), a countdown sound began playing and the green pole started turning red (see Fig. 8). Once the 3-second countdown was finished and the green pole had completely turned red, the poles disappeared and the ball was launched. A trial was counted as successful if the ball was within a radius of 0.35 m around the center of the baseball glove. In that case, an applause sound was played and the next blue and green poles for the following trial appeared. If the ball was not successfully caught, the next trial started as soon as the ball was out of reach (i.e. outside of the rectangle defined by the room's dimensions).

Each participant had to complete 100 trials, of which the first 4 were practice trials. The remaining 96 experimental trials were grouped into 3 blocks of 32. In each block, the contrast of the ball during a trial was varied as a different function of time $f(t)$:

Constant: In the constant contrast condition, the ball was always perfectly visible:

$$f(t) = 0.8c, \tag{3}$$

where c was 1 for the first 16 trials in the block and 0.2 for the other 16.

Bearing velocity: In this condition, the contrast of the ball changed with the velocity of the bearing angle $\dot{\psi}(t)$ (see Fig. 5), such that it was impossible to see for constant bearing angles and easier to see for higher bearing angle velocities. This was realized by applying a logistic sigmoid function to the bearing angle velocity. The logistic sigmoid is the function $\sigma(x) = \frac{1}{1+exp\{-k(x-x_0)\}}$. In this experiment, the parameters were determined empirically with the aim to make the ball impossible to see when the bearing angle was kept constant while still allowing subjects to successfully catch every ball: $k = 1.5$ and $x_0 = 7$.

If the contrast only depends on this sigmoid function, it is really easy to see the ball towards the end of the trial even if a constant bearing angle were maintained throughout a trial, since the change in bearing angle depends on the distance between the ball and the subject. A ball at a small distance results in a higher bearing angle velocity than a ball at a larger distance moving at the same velocity. To account for this (i.e. to make the ball harder to see when it is closer to the subject), the sigmoid function was multiplied by a term that depends on the current distance between the subject and the ball $d(t)$ relative to the initial distance at the start of the trial:

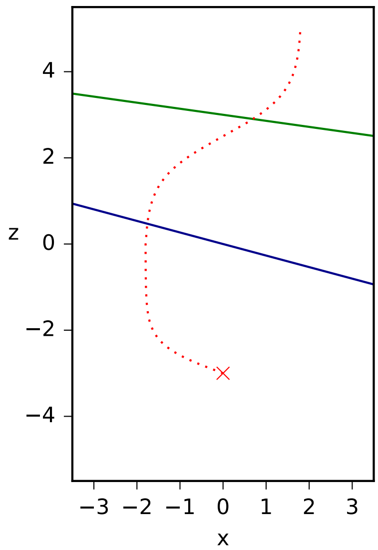
$$f(t) = 0.8\,\sigma(\dot{\psi}(t))\,(f_{min} + \frac{(1-f_{min})\,d(t)}{d_0}), \tag{4}$$

where d_0 is the initial distance between subject and ball and $f_{min} = 0.01$. The bearing velocity $\dot{\psi}(t)$ was computed after smoothing the bearing angle signal on-line by applying an exponentially weighted moving average filter with a smoothing factor of 0.3.

Fixed path: In the fixed path condition, the contrast varied as a function of the subject's distance to a specific path in the xz-plane (see Fig. 9). The x coordinate of the path was computed according to this function:

$$x(z) = \begin{cases} -1.8\ \tanh(1.5\,(z+3)) & \text{for } z < 0 \\ 1.8\ \tanh(1.5\,(z-2.5)) & \text{for } z \geq 0 \end{cases} \tag{5}$$

Figure 9: The path that participants had to follow in order to perfectly see the ball in the *fixed path* condition.



The path shown in Fig. 9 was used for balls coming from the left starting point. For balls coming from the right, the path was mirrored across the z axis by multiplying the x component by −1. The contrast of the ball was then computed as a function of the shortest Euclidean distance $d(t)$ between the subject and that path:

$$f(t) = 0.8\,(1-\sigma(d(t))), \tag{6}$$

where σ is again the logistic sigmoid function, in this case with $k = 15$ and $x_0 = 0.4$.

The third block was always the *constant* contrast condition. This deviation from a completely counterbalanced design was chosen since previous runs of the experiment had shown that after completing the *constant* contrast condition, most subjects had learned a spatiotemporal strategy and knew where in the room to catch balls even if they could not see them in the other two conditions, thus making visual information from the ball less important. We aimed to prevent this kind of effect by placing the trials with constant contrast at the end of the experiment. The order of the first two blocks (*fixed path* and *bearing velocity*), however, was counterbalanced between participants.

2.5 Data analysis

Due to latencies in the wireless transmission of PPT data to the laptop, sometimes the recorded positions of two consecutive time steps were equal. To overcome the effects of this and to reduce other sources of noise, position data were filtered prior to computing the subject's velocities. For this, a 4th order Butterworth filter with a cutoff frequency of 2.4 Hz was used.

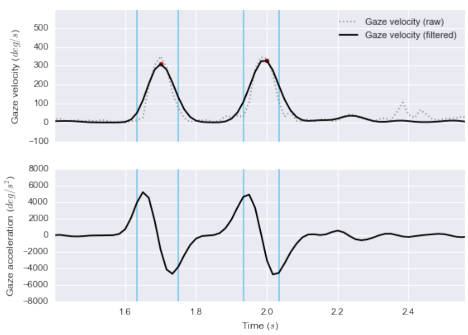
The bearing angle was computed as the horizontal angle defined by the positive z axis, the player, and the ball. In order to compute the heading angle (the angle of the subject's movement direction w.r.t. the positive z axis) from velocity data, the position data were filtered as described above. Whenever angular velocities were computed, the angle was filtered using a 3rd-order Saviztky-Golay filter with a window length of 7. The velocity was then computed as the first time derivative of the polynomial obtained by the filter.

The eye tracking data were preprocessed and gaze shifts were detected following the example set by Diaz, Cooper, Kit, and Hayhoe (2013). However, since we recorded the gaze vector in world coordinates instead of pixel values in screen coordinates, a 3-unit-wide median filter was applied to the gaze vector (instead of the pixel values), followed by a Gaussian 3-unit-wide Gaussian filter. After that, the gaze vector was normalized again. From these filtered data, the gaze velocity was calculated by numerical differentiation according to:

$$g_{vel} = \frac{\cos^{-1}(\mathbf{g_t} \cdot \mathbf{g_{t-1}})}{\Delta t}, \tag{7}$$

where $\mathbf{g_t}$ is the gaze vector at time step t. Since the gaze vector incorporates movements of the head as well as the eyes, big shifts in the gaze vector can be interpreted as coordinated movements of head and eyes. To reduce noise in the data, the gaze velocity was then convoluted with a kernel that is representative of a saccade. Since the kernel used by Diaz, Cooper, Kit, and Hayhoe (2013) amplified the signal too much, the kernel [0, 0.25, 0.5, 0.75, 0.5, 0.25, 0] was adopted. The gaze shifts were then detected as local maxima with a value higher than 100°/s in the gaze velocity signal. The start and end of the gaze shift were determined as the frames before/after the local maxima/minima in gaze acceleration around the peak in velocity (see Fig. 10).

Figure 10: An example of the gaze shift detection. The blue lines indicate start and end of a gaze shift and the red dot indicates the peak.

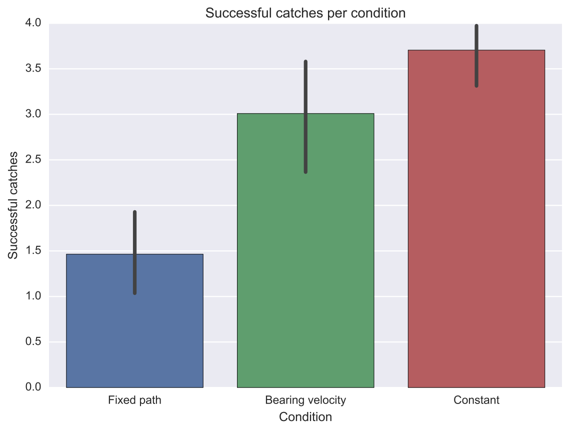


3 Results

3.1 Successful catches

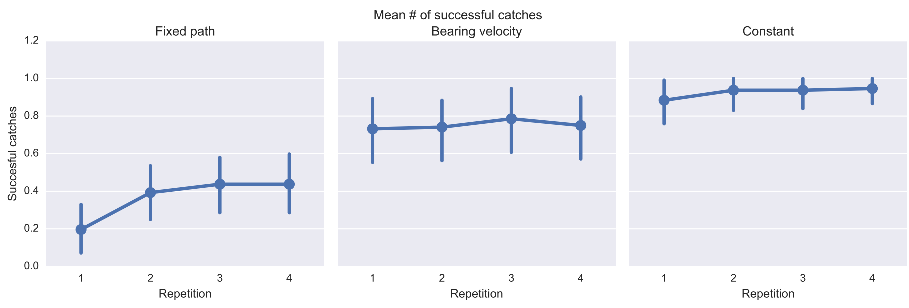
A trial was counted as successful if the minimum distance between the glove and the ball was lower than 0.5 m at any point during the trial. This corresponds to a 0.35 m radius around the glove's center plus the ball's radius of 0.15 m. The total success rate across all participants and conditions was 0.68 (SD = 0.19), while individual success rates ranged from 0.27 to 0.86. The mean number of successful catches per condition can be seen in Figure 11. Subjects managed to catch most of the balls in both the *constant contrast* and the *bearing velocity* condition. However, most of the subjects were not very successful in the *fixed path* condition. Only four out of all participants (subjects 2, 9, 12 and 13) managed to catch more than half of the balls in that condition. A repeated measures ANOVA was conducted to compare the effect of contrast condition, ball start location (left or right), ball direction (near or far) and ball speed (4.5 or 5.5 m/s) on the number of successful catches. Significant effects were found for contrast condition ($F(2,26) = 40.44, p < 0.001, \eta^2 = 0.76$), ball direction ($F(1,13) = 7.72, p = 0.016, \eta^2 = 0.37$) and ball speed ($F(1,13) = 14.61, p = 0.002, \eta^2 = 0.53$). The effect of the ball's initial location was not significant and neither were any interactions between the independent variables. These results show that the balls that were faster or further away were harder to catch and that especially the *fixed path* condition was difficult for the participants. Additionally, we tested whether there were differences in interception success between the two contrast levels in the *constant contrast* condition, which was not the case ($F(1,13) = 2.33, p = 0.151$).

Figure 11: Mean number of successful catches per condition. Error bars represent between-subjects 95% confidence intervals. Since there were four repetitions of each trial, the maximum number of successful trials is four.



Three subjects (6, 10 and 14) did not catch more than half of the balls in total and reported difficulties in getting accustomed to the VR setup. All of them stated that they were afraid of running into the walls of the room, which were not visible in the virtual environment. Their data were therefore discarded and excluded from all following results. A look at the interception performance over the course of the four repetitions (see Fig. 12) reveals that, while interception performance was constant in the *constant* and *bearing velocity* condition, some subjects improved in the *fixed path* condition, which suggests they learned some kind of strategy to catch the balls. An increase in successful catches resulting in an interception rate of 50% or higher for the second half of the *fixed path* condition was found in subject 2, 5, 8, 9, 12 and 13.

Figure 12: Mean number of successful catches per and repetition. Error bars represent between-subjects 95% confidence intervals. For individual plots per subject see Appendix B



3.2 Trial duration and subject velocities

For all following results, only trials in which the participant successfully caught the ball were considered, unless stated otherwise. The mean trial duration was 4.73 seconds, with a standard deviation of 0.50. To obtain an estimate of the subjects' speed, we computed the mean speed between the 1-second mark and the 4-second mark of each trial. Subjects ran to intercept the balls at a mean speed of 1.13 m/s (SD = 0.42). This value is comparable to similar studies in virtual and real environments (see Table 1), although it is on the lower end of the spectrum.

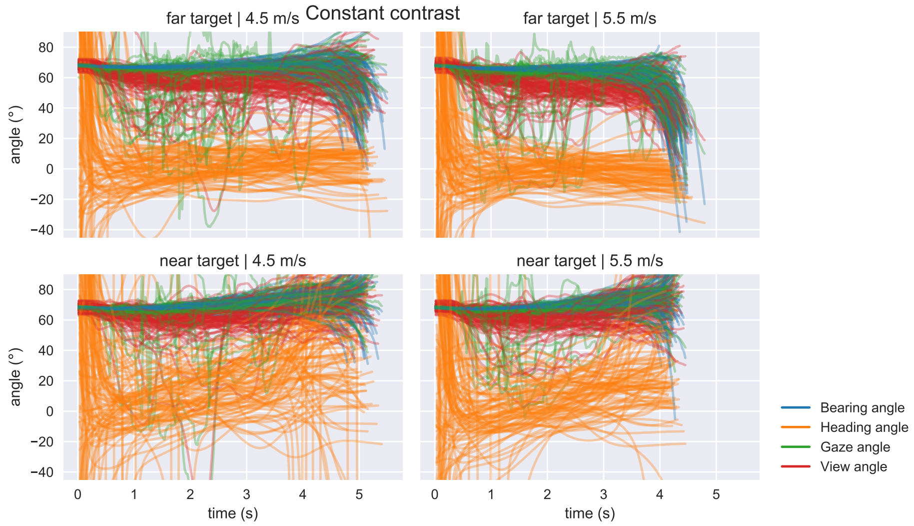
3.3 Relationship between heading, gaze and bearing angle

A common limitation of experiments in virtual environments on screens is that the direction of heading and the view direction are usually coupled. To examine whether this is the case in a more natural environment, the root mean squared error (RMSE) between the heading angle and the view angle (i.e. the horizontal component of the orientation of a subject's head) was computed for every trial. Only trials from the *constant* contrast condition were considered because the ball was not permanently visible in the other two conditions (see Section 3.6). The mean RMSE between heading and view direction across trials was 56.95 degrees (SD = 14.55). This implies that the view direction is generally not equal to the direction of heading. It should be noted, however, that the design of the present experiment favored large differences between view and heading angle since the balls were launched from the sides and subjects had to move forwards in order to catch the ball within the dimensions of the lab. This means that the view direction inevitably differs from the heading direction if one looks at the ball. The large deviations between view direction and heading direction, therefore, suggest

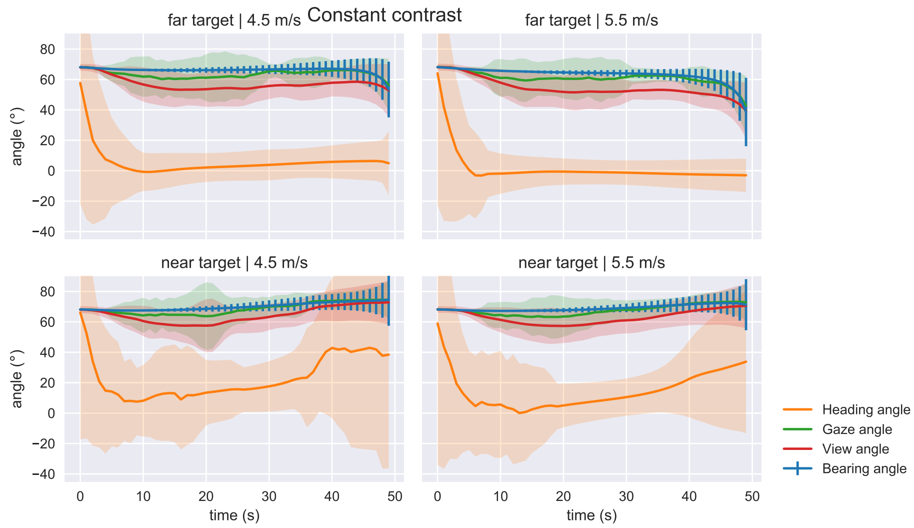
Figure 13: Gaze, view, bearing and heading angles in a typical trial from the experiment (subject 7, trial 80). The contrast condition was *constant*, ball speed was 5.5 m/s and the ball direction was *far*. The subject fixated the ball throughout the trial with their view direction slightly ahead of the ball, keeping the bearing angle constant and walking on a straight path (constant heading angle).

that subjects looked at the ball most of the time. This is indeed the case for most trials (see Fig. 13 for an example). Due to hardware issues, no eye tracking data were recorded for subject 1, whose data are excluded from the following results in this section. Figure 14 shows the gaze, heading, view and bearing angles for all successful trials in the *constant* contrast condition as well as average angles across trials. The data were aggregated by normalizing the time of each trial to 50 bins, computing the mean angles for each of the bins and averaging across trials from all subjects for each condition. Like in the single trial presented above, the bearing angle (i.e. the direction of the ball w.r.t. the z axis) was approximately constant for most trials and its variability across trials was low. The difference between the horizontal gaze angle and the bearing angle was lower than 3 degrees in 84% of all time steps, indicating that subjects followed the ball with their gaze most of the time. To further investigate this result, the number of shifts in gaze direction (see Section 2.5) per trial was computed. Since only very few gaze shifts per trial were observed (M = 1.73, SD = 2.86), this supports the hypothesis that subjects followed the ball with their gaze most of the time. However, the gaze direction occasionally shifted away

Figure 14: Gaze, heading, view and bearing angles from all trials in the *constant* contrast condition.



(a) Each individual trial



(b) Means of normalized data. Shaded areas and error bars represent standard deviations across trials from all subjects.

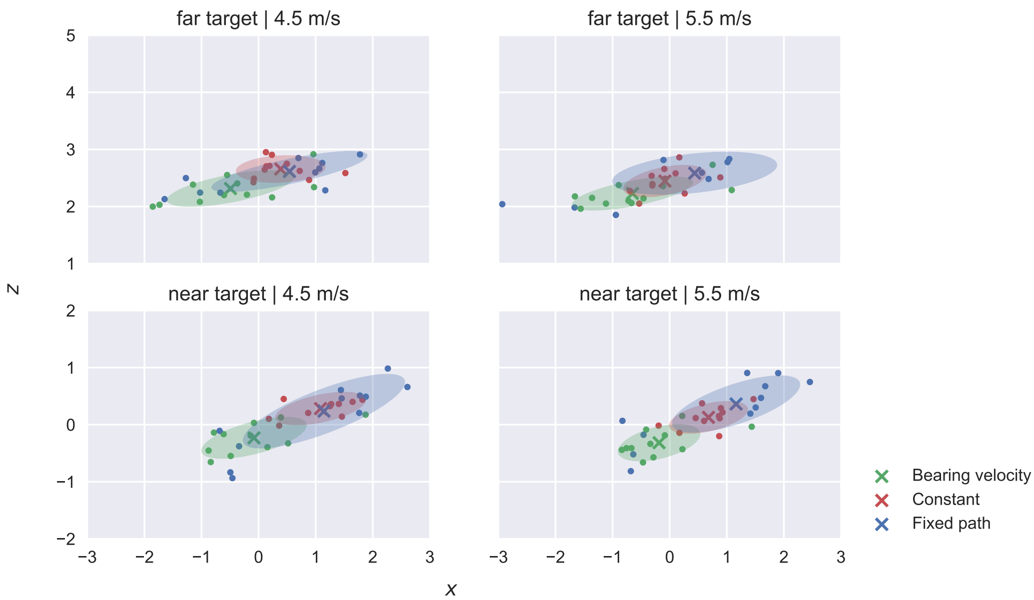
from the ball and towards the heading direction for a short amount of time, hence the larger standard deviation of the gaze angle. The view angle was slightly lower than the bearing and gaze angles most of the time, which means that the view direction (the orientation of the subject's head) was somewhat ahead of the ball. The direction of movement (the heading angle) was also approximately constant in the *far* target condition, indicating that subjects moved on a straight path to intercept the ball. For the *near* targets, there is more variability in the heading angle, especially in the later phase of the trials. Possible reasons for these deviations from a constant heading angle are discussed in Section 3.5.1.

3.4 Interception locations

In order to find differences in interception strategies, the final position of the viewpoint (defined by the PPT marker attached to the Oculus Rift) was examined. Since repeated measures ANOVAs of the initial ball location (left, right) on the final x position ($F(1,10) = 0.20, p = 0.664$) and the final z position ($F(1,10) = 2.02, p = 0.186$) did not indicate significant differences, the data for balls coming from the left were flipped along the z axis, so that all balls were treated like they were launched from the right side. These collapsed data were used for the following analyses. Like for the interception success, there were also no significant differences in the final interception location between

Figure 15: Final locations (i.e. view point position at the time of minimum distance between glove and ball) for all trials, grouped by ball direction and speed. Positions from trials in which the ball started from the left of the participant are flipped to be comparable to the rest of the trials.

Figure 16: Mean final locations across all trials (indicated by the x's in the plot) and means per subject (indicated by the dots) grouped by ball direction and speed. The ellipses illustrate the covariance of two-dimensional Gaussian distributions fit to the data (1 standard deviation in the direction of the eigenvectors of the covariance matrix).



the two contrast levels within the *constant* contrast condition ($F(1,10) = 0.25, p = 0.627$ for the final x position; $F(1,10) = 0.28, p = 0.611$ for the final z position). Thus, we chose to treat all trials from the *constant* contrast condition as one condition. The final locations for all successful trials are shown in Figure 15. Note that the variability of the final locations is large in all three conditions. Nevertheless, there are noticeable differences in final interception locations between the three conditions. For one thing, balls in the *bearing velocity* condition were caught in the later part of the ball's trajectory. This can be best explained by the fact that the balls were not visible at the start of the trial in that condition until the bearing velocity reached a certain threshold (if the subject did not run in a way that would lead to earlier changes in bearing velocity; see Section 3.5.2). Therefore, participants had less time to catch the ball, resulting in a later interception. And for another thing, most of the trials in which the final location was close to the early parts of the ball's trajectory are from the *fixed path* condition. This seems reasonable, since the path that participants had to follow in order to see the ball leads towards the earlier parts of the ball's trajectory. The higher number of final locations from the *fixed path* condition in that area indicates that at least some of the subjects employed a strategy based on maintaining visibility of the ball by walking towards the right side of the room.

An inspection of the mean interception locations per subject and across all subjects (Fig. 16) confirms these suspicions. The mean final location of the *bearing velocity* condition is clearly shifted to the left w.r.t. to the trials from the *constant* contrast condition for all target conditions. For the *fixed path* condition, the variance of the final locations is higher. While the mean interception location is shifted to the right for some subjects, other subjects caught the ball more to the left of the room.

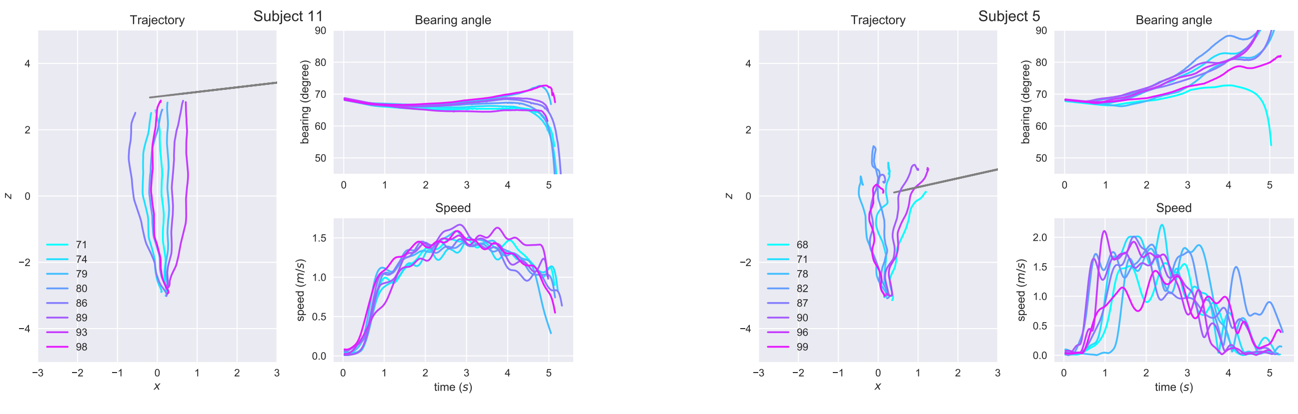
3.5 Interception strategies

To investigate the cause of the observed differences in the final interception location, we now take a look at the trajectories that the subjects walked along. Since subjects varied greatly in terms of interception performance and also in terms of their interception locations, it is necessary to look at the trajectories of each subject individually. Plots of trajectories, bearing angles and velocity profiles for every subject in every condition can be found in Section C of the Appendix. In this section, a few plots from different subjects will be discussed to exemplify the different strategies used across subjects and contrast conditions.

3.5.1 Constant contrast condition

For most subjects, the trajectories in the *constant* contrast condition look similar to the ones in Fig. 17 a). Subjects moved on a roughly straight path and accelerated until they reached a speed that allowed them to maintain a constant bearing angle. To illustrate how the velocity of the bearing angle changed over time, each trial was truncated after the subject had reached a distance of 2 m to the ball. This was necessary to eliminate

Figure 17: Trajectories, bearing angles and velocity profiles in the *constant* contrast condition.

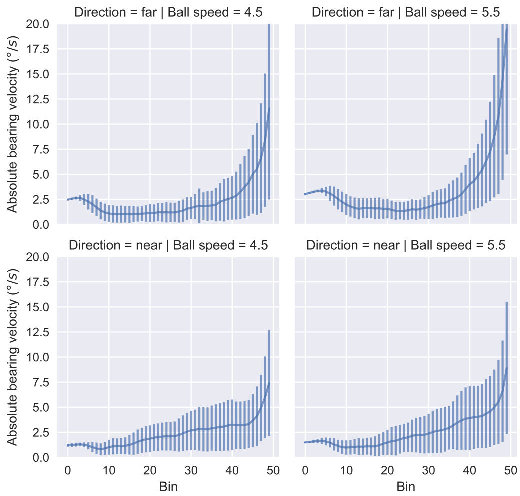


(a) Subject 11 in the *constant* contrast, *far* target condition with a ball speed of 4.5 m/s.

(b) Subject 5 in the *constant* contrast, *near* target condition with a ball speed of 4.5 m/s. This subject moved faster than predicted by a CBA strategy, even exceeding the z component of the ball's trajectory, and then decelerated. This leads to an increasing bearing angle. Similar patterns were observed for subjects 7 and 13 in the same condition.

the explosion of the bearing velocity towards the end of each trial due to the low distance between the subject and the ball. The data were then normalized and averaged as described in Section 3.3 (see Fig. 18). Because deviations from a constant bearing angle can either mean an increasing or a decreasing bearing angle, averaging bearing velocities across trials would possibly cancel out positive and negative deviations. Thus, we used the absolute bearing velocity. The absolute bearing velocity is below 3 degrees for most time steps and its standard deviation is rather low, which suggests that the bearing angle was held constant consistently for most trials in the *constant* contrast condition. However, even in this condition, considerable deviations from CBA were observed in some trials (e.g. Fig 17 b)). Most trials like these, which show an increasing bearing angle, occurred in the *near* target condition with slow target speed. This suggests that subjects were able to move to the expected interception point faster than by keeping a CBA and then wait there for the ball to arrive, which is consistent with oral reports by the subjects after the experiment. This kind of behavior can also be understood as one cause for the deviations from a constant heading angle mentioned in Section 3.3. Once a subject stands still or moves really slowly, there is no clear information about the direction of movement and the estimation of the heading angle from the subject's velocity does not produce reliable values, resulting in deviations from a constant heading angle as well as larger standard deviations.

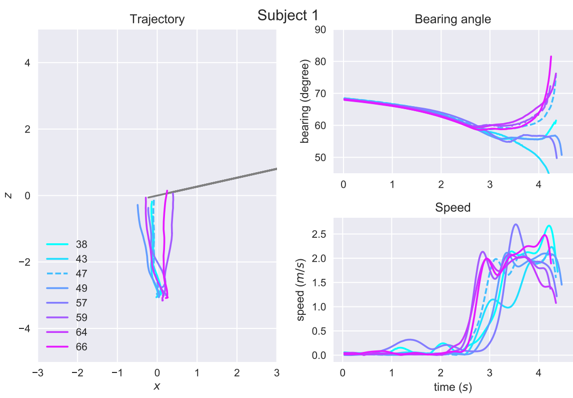
Figure 18: Mean absolute bearing angle velocity in the *constant* contrast condition. The data were averaged after normalizing to 50 bins. Error bars represent standard deviations.



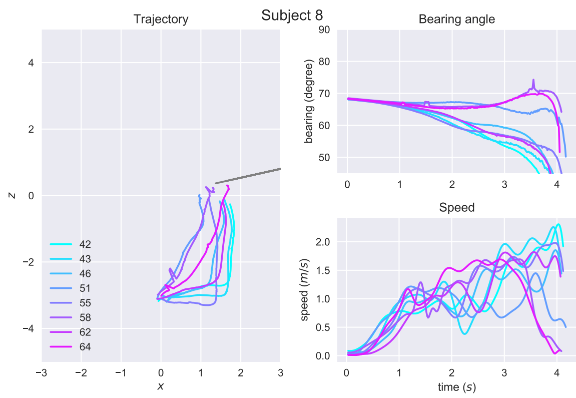
3.5.2 Bearing velocity condition

The first difference from the *constant* contrast condition that meets the eye when looking at typical trials from the *bearing velocity* condition (e.g. Fig. 19 a)) is that the subject's speed was close to 0 during the initial few seconds of each trial. This observation can be attributed to the low contrast of the ball at the start of each trial in this

Figure 19: Trajectories, bearing angles and velocity profiles in the *bearing velocity* condition. Broken lines indicate unsuccessful trials.



(a) Subject 1 in the *bearing velocity*, *near* target condition with a ball speed of 5.5 m/s.



(b) Subject 8 in the *bearing velocity*, *far* target condition with a ball speed of 5.5 m/s.

condition. The ball's contrast depended on the bearing velocity and the initial bearing angle velocity was not high enough to make the ball clearly visible by design of the experiment. If the subject simply waited, the ball became visible after a few seconds, when the relative movement of the ball with respect to the subject leads to an increasing bearing velocity. This means that subjects actively had to walk in a way that leads to higher bearing angle velocities if they wanted to see the ball earlier. However, the low subject velocities during the initial 2 seconds in this condition (M = 0.21 m/s, SD = 0.22) indicate that subjects did not generally employ a strategy that actively aims to increase the bearing velocity in order to see the ball earlier. Instead, almost all subjects waited until the bearing velocity increased enough for them to get a good observation of the ball and then started running on a straight path. This is illustrated in Fig. 20, which shows the mean bearing velocity of the normalized data. The mean bearing velocity increases until it reaches a value of approximately 5 °/s. After that (when to subjects started running to intercept the ball), the bearing velocity decreased again. The implications of this kind of behavior on the ball contrast are discussed in Section 3.6. Some of the subjects, however, did show behavior that differs substantially from the straight paths observed in the other subjects. For example, subject 8 did not stand still until the ball became visible on its own, but rather started moving sideways towards the ball (see Fig. 19 b)) and thereby increased the bearing velocity earlier (see Fig. 21), leading to earlier visibility of the ball. Similar behavior (although not as consistent) could be observed in subject 13, who also moved sideways in some trials (although in the opposite direction, away from the ball) instead of waiting for the ball to appear.

Figure 20: Mean absolute bearing angle velocity in the *bearing velocity* condition. The data were averaged after normalizing to 50 bins. Error bars represent standard deviations.

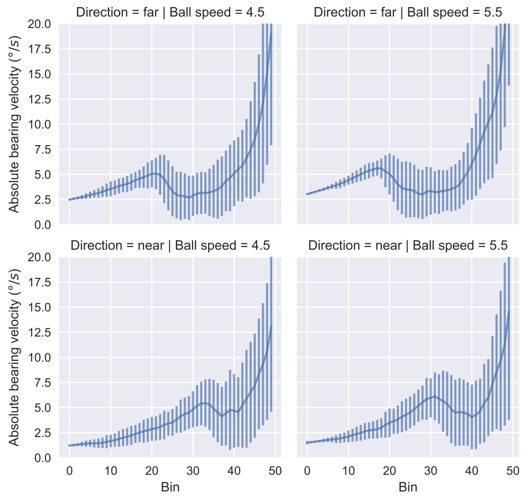
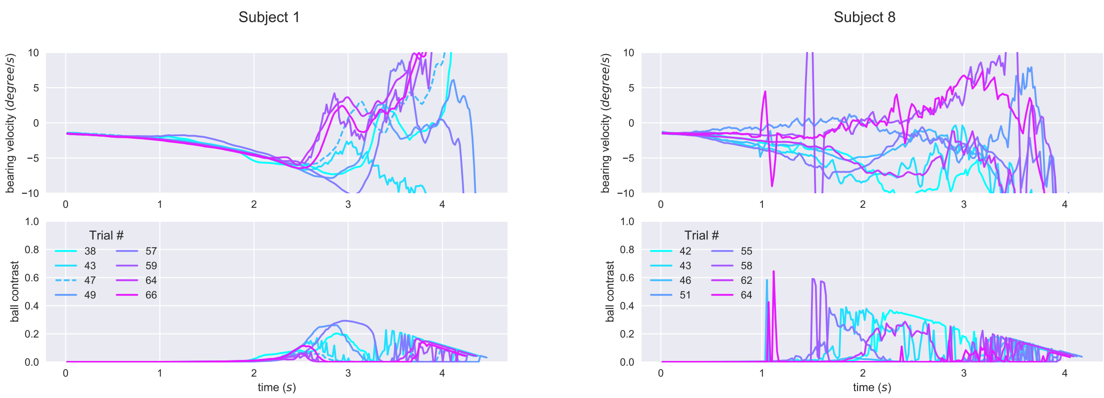


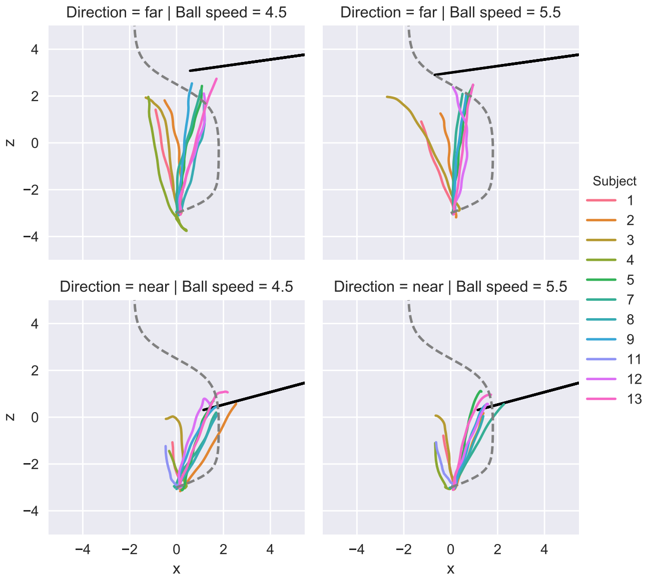
Figure 21: Bearing velocities and ball contrast of subjects 1 and 8 in the *bearing velocity*, *near* target condition with a ball speed of 5.5 m/s. Compared to subject 1 (and most other subjects), the bearing velocity of subject 8 increased earlier, leading to an earlier increase in ball contrast. These kind of plots for all other subjects and conditions are included in Appendix C.



3.5.3 Fixed path condition

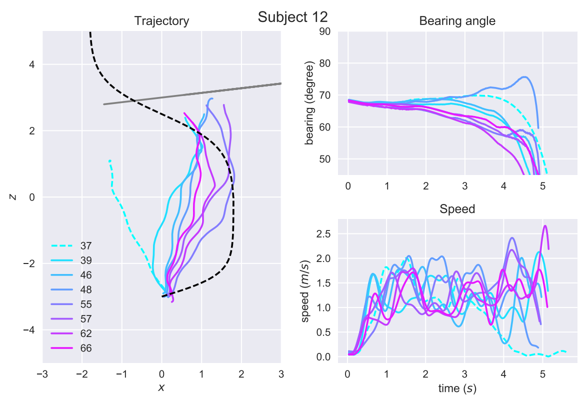
As indicated by the low success rates, most of the experimental subjects failed to find a way to cope with the unusual change of target visibility in the *fixed path* condition. Since only subjects 2, 5, 8, 9, 12, and 13 caught at least half of the balls in the second half of this condition, we only consider these subjects in this section. All of the other subjects reported that they did not notice that the ball's contrast was in any way connected to their own actions. While the above-mentioned successful subjects reported that they noticed a connection between their own behavior and the ball's visibility, none of them were aware that there was a specific path they could follow that allowed for perfect visibility of the ball. To get an idea about how the more successful subjects differed from the less successful ones, average trajectories of each subject in the *fixed path* condition are presented in Fig. 22. These were computed using the normalized data by averaging the x as well as z positions across trials at every time step. One can see that the more successful subjects'

Figure 22: Average trajectories per subject in the *fixed path* condition. In some target conditions there are missing subjects because not every subject caught a ball in every condition

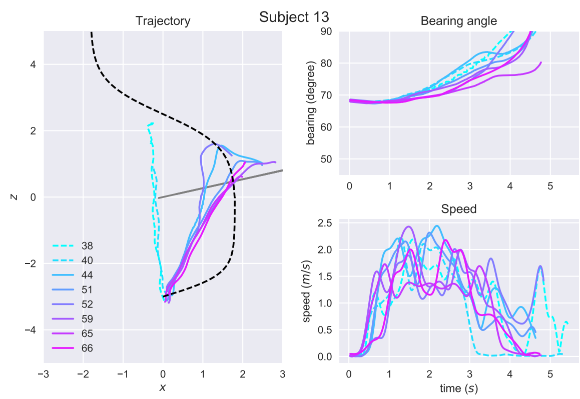


mean trajectories are slanted to the right, while the trajectories of the less successful subjects are slanted to the left. This implies that the subjects who performed better had a tendency to walk to the right, where they were more likely to see the ball. While these mean trajectories are suggestive of differences between subjects, it should be noted that the trajectories also differ heavily within subjects. For this reason, we take a closer look at some trials from the more successful subjects. Although none of the subjects closely followed the fixed path, which would have enabled them to perfectly see the ball during the whole trial, they all approached or crossed the path again before catching the ball. An example is depicted in Fig. 23 a). One can see that the first trial in that condition was not successful since the subject had no chance to see the ball during the later phase of the trial. However, in the following trials, the subject walked more towards the right side

Figure 23: Trajectories, bearing angles and velocity profiles in the *fixed path* condition.



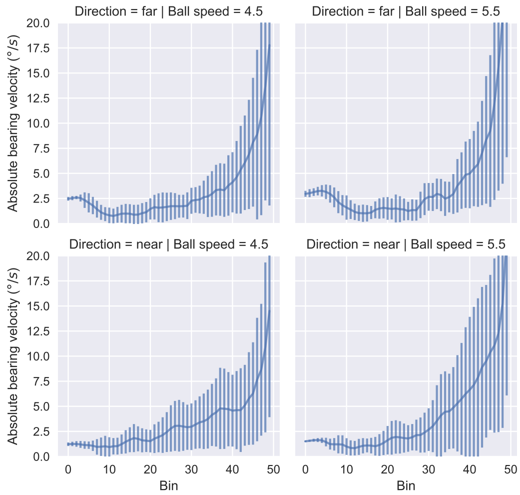
(a) Subject 12 in the *fixed path*, *far* target condition with a ball speed of 4.5 m/s.



(b) Subject 13 in the *fixed path*, *near* target condition with a ball speed of 4.5 m/s.

of the room, where the fixed path was located. They could therefore see the ball again later in the trial and successfully catch the ball. Similar tendencies are present in all of the more successful subjects in the *fixed path* condition. This result suggests that some of the subjects were able to adjust their behavior in order to overcome the difficulties posed by the varying ball contrast. Although there are clear differences in behavior compared to the *constant* contrast condition, these do not imply larger deviations from CBA (see Fig. 24). Like in the *constant* contrast condition, the mean bearing velocity in the *far* target condition is below 3 °/s for most time steps. For the *near* target condition, however, there is a stronger

Figure 24: Mean absolute bearing angle velocity in the *fixed path* condition. The data were averaged after normalizing to 50 bins. Error bars represent standard deviations.



increase in the bearing velocity. This can be explained by taking a closer look at typical trajectories from that condition (see Fig. 23 b)). After two failed trials, the subject seemed to notice that there is an area in the room which enables them to see the ball. In the following trials, they walked to that area, regardless of whether the next ball would be from the *near* or *far* target condition, and then moved towards the ball as soon as it became visible. This behavior resulted in an increasing bearing angle for the *near* balls (for which the subjects walked ahead of the ball in the z direction and then had to turn around in order to catch the ball) and could also be observed in subjects 5, 9 and 12.

3.6 Ball contrast

Since the ball's contrast changed depending on the subjects' behavior (as illustrated in Fig. 21), large differences in ball contrast between the conditions were possible in this experiment. To investigate these differences, the mean ball contrast for each successful trial (between the 1 and 4-second mark) was computed. The means of these values per condition and subject are presented in Fig. 25. The mean contrast in the *constant* contrast condition is approximately 0.48 for all subjects, which corresponds to the mean of the two constant contrast levels. Deviations from this value are due to the few unsuccessful trials in that condition. The mean contrast in the *bearing velocity* condition is significantly lower than in the *constant* contrast condition for all subjects, which indicates that the ball was poorly visible most of the time. This result is somewhat surprising since subjects nevertheless managed to

Figure 25: Mean ball contrast (between the 1 and 4-second mark of each trial) for every subject and condition. Error bars represent 95% confidence intervals.

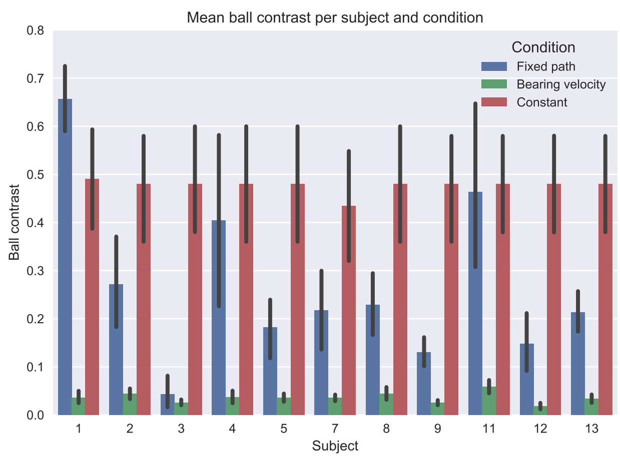
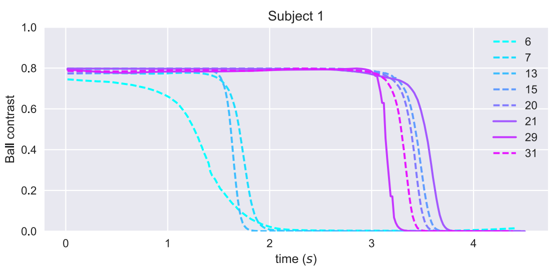


Figure 26: Mean ball contrast over time for successful trials in the bearing velocity condition. Error bars represent standard deviations.

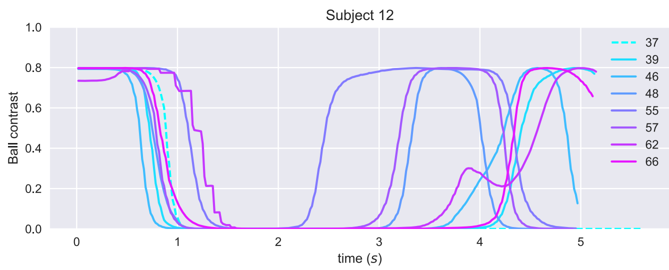
catch the balls better than in the *fixed path* condition. To get an idea of how the ball contrast changed over time, the data were binned as described in Section 3.3 and the mean ball color for each bin was computed. The data were then averaged on the subject level (see Fig. 26). The mean contrast was very low during the initial phase of the trial until the ball became visible due to a rise in bearing velocity (as described in Section 3.5.2). The contrast then went to zero again for almost all of the subjects, because they started moving in a way that decreased the bearing velocity. Towards the end of the trial, the ball became visible again, which inevitably happens if the subject's distance to the ball is low enough. Due to the definition of the bearing angle, the bearing velocity explodes when the ball moves with some horizontal speed and is close to the subject. This enabled subjects to see the ball again and finally catch it even if they did not see it during the middle part of the trial. This result suggests that a short observation of the ball is sufficient for a successful interception, as long as the ball becomes visible again before catching. However, the large standard deviations indicate that there are big differences within subjects in terms of their behavior in the *bearing velocity* condition.

In the *fixed path* condition, there are bigger differences in the mean ball contrast between subjects. Somewhat surprisingly, the successful subjects in this condition (5, 8, 9, 12 and 13) are not among the ones with the highest mean contrast. Subjects 1, 3, 4 and 11 have a particularly high mean contrast. To examine why this is the case, we take a look at some exemplary trials. Since there were a lot less successful trials in the *fixed path* condition than in the *bearing velocity* condition and there was a lot more variability between trials, averaging across trials could not be considered sensible. Fig. 27 a) shows the contrast in typical trials of subject 1 (subjects 3, 4 and 11 are similar). They waited at their start location, allowing them to see the ball for quite some time (since the start location belongs to the fixed path). Then they started running and tried to intercept the ball with their hand without actually seeing it during the later phase of the trial. The more successful subjects, however, show a lower mean ball contrast due to the behavior discussed in Section

Figure 27: Ball contrast over time in the *fixed path* condition.



(a) Subject 1 in the *fixed path*, *near* target condition with a ball speed of 5.5 m/s. The subject waited at their start location (which enabled them to see the ball) and then started running and blindly caught the ball in some trials. However, the many unsuccessful trials (broken lines) indicate that this was not the most efficient strategy.



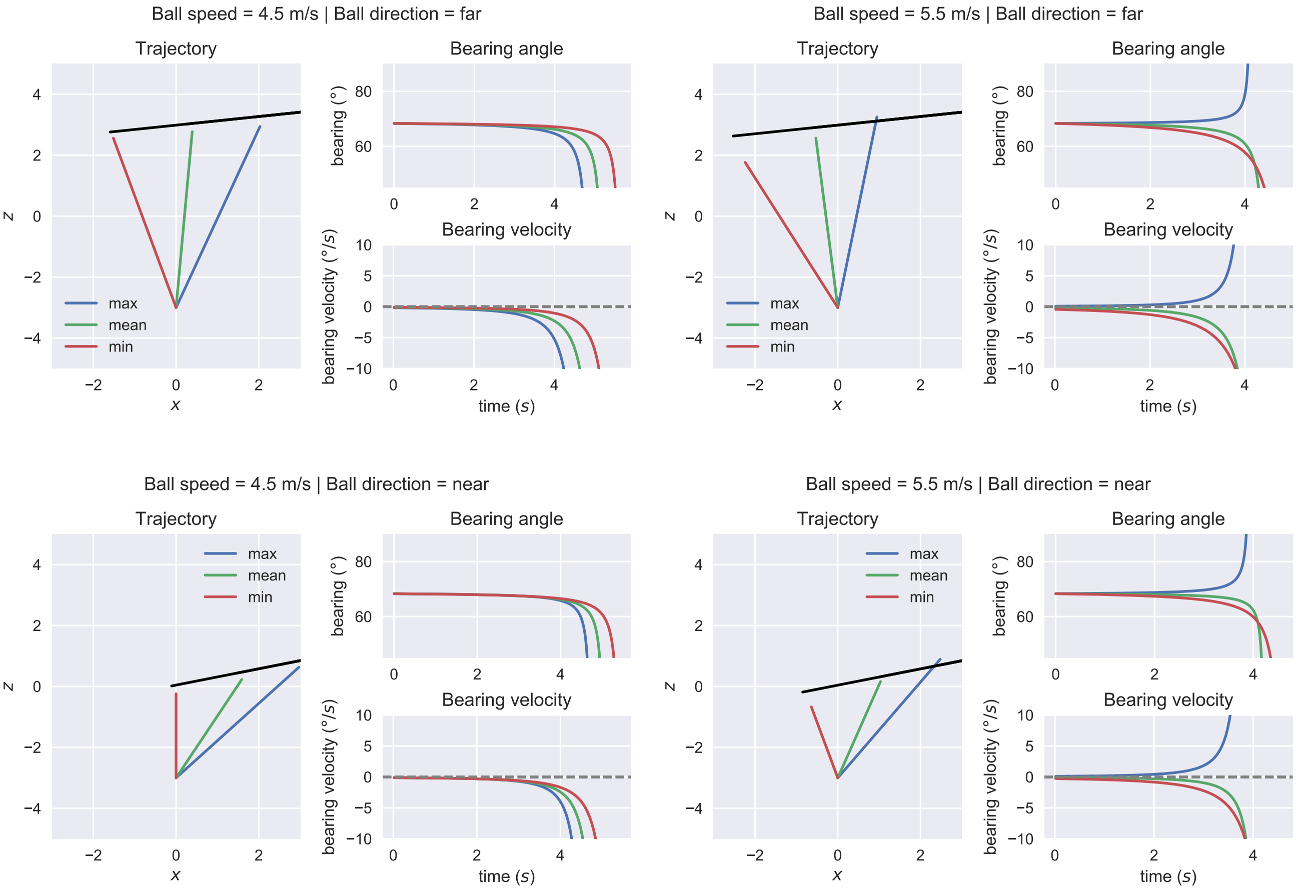
(b) Subject 12 in the *fixed path*, *far* target condition with a ball speed of 4.5 m/s (the same condition as in Fig. 23). The subject left the path (resulting in a decreasing contrast) but approached the path again later in the trial, which enabled them to see the ball before catching.

3.5.3. These subjects left the path, which leads to a low ball contrast during the middle of the trial, but walked towards the right side of the room to cross or approach the path later during the trial. That way they could see the ball again and catch it a lot more often. Fig. 27 b) shows the contrast over the course of some trials in which the subject exhibited this kind of behavior. Since the ball was not visible during the middle phase of the trial, this results in a lower mean contrast but represents a much more successful strategy.

3.7 Simulated trajectories with constant velocities

For a better understanding of the relationship between the subjects' movements and the bearing angle, we computed simulated trajectories for an agent that walks at a constant velocity. In order to obtain velocities comparable to the ones observed in the experiment, we computed the mean subject velocity for each successful trial in the *constant* contrast condition. For each target condition (target speed and target direction), we then used the minimum and maximum velocity across subjects, along with the mean of these two values. These three velocities were then used to construct trajectories of an agent that simply moves at these velocities throughout the whole trial (see Fig. 28). All these simulated

Figure 28: Trajectories, bearing angles and bearing velocities of an agent that moves at a constant velocity, which is either the minimum, the maximum or the mean of the minimum and maximum velocities of all subjects in that condition. Broken lines indicate unsuccessful trials, in which the minimum distance between agent and ball was larger than 0.5 m.



trials result in successful catches, since the final distance between the agent and the ball is lower than 1 m (and thus shorter than one arm's length) in all conditions. The bearing angle is almost perfectly constant for all of the simulated trajectories, as illustrated by the bearing velocity, which is very close to 0 °/s for most part of each trial. The bearing velocity only increases or decreases as soon as the agent gets close to intercepting the target. This happens earlier if the agent is fast (and therefore catches the ball sooner) and later if the agent is slower.

4 Discussion

Consistent with previous findings (e.g. Chardenon, Montagne, Laurent, & Bootsma, 2005; Fajen & Warren, 2007), this study shows that under normal conditions, in which the target is permanently visible and moves at a constant velocity, humans maintain a constant bearing angle. The subjects in this study kept their view direction slightly ahead of the ball while pursuing the ball with their eyes almost all of the time. The difference between the view direction and the direction of movement was large, which underlines the importance of experimental designs that do not couple the two (like on-screen VR environments usually do). Subjects walked on a roughly straight path to intercept the target, although the variability of the heading angle was substantially larger than for the bearing angle and gaze angle. It is, however, not clear if this larger variability is indicative of a behavioral strategy based on controlling the bearing angle rather than the heading angle, or if it can be explained by the fact that the heading angle needs to be estimated from the first time derivative of the subject's position (which introduces additional noise), while the bearing angle can be directly computed from position data. The success rate was almost perfect in this condition, which shows that catching perfectly visible balls moving at a constant velocity is a rather easy task for humans. Although behavior in the *constant* contrast condition was for the most part consistent with the CBA strategy, there were nevertheless some trials in which subjects deviated considerably from the CBA strategy. These deviations most noticeably occurred when the ball was very easy to catch (i.e. balls that crossed the room close to the subject's initial position and move at a low speed). There is evidence that the CBA strategy is not suitable to explain behavior when the speed required to maintain a CBA is above an actor's maximal speed (Bastin et al., 2010). Similarly, the deviations from CBA for slow targets indicate that the CBA strategy might not be suitable to explain behavior when the required speed for a CBA is very low.

Performance in the *bearing velocity* condition, in which the contrast of the ball increased with the bearing velocity, was only slightly worse than in the *constant contrast* condition. This contrast manipulation elicited clear changes in the bearing angle during the early phase of the trials, which can, however, be explained by the low initial bearing velocity, that made the ball practically invisible at the beginning of the trials in this condition. Without seeing the ball, subjects did not have access to the bearing angle and thus could not control their actions in a way that keeps the bearing angle constant. Instead, they waited for the bearing velocity to increase until the ball appeared and then started running. This left them with a shorter amount of time for the interception, resulting in interception locations that were shifted towards the later parts of the ball trajectory compared those in the *constant* contrast condition. As soon as the subjects started running on a straight path to intercept the ball, the bearing velocity (and hence the ball contrast) decreased again. Thus, the mean contrast went to zero during the middle part of the trials for most subjects. This means that the ball was invisible for some time in most trials. It appeared again before interception due to an increase in the bearing velocity, which inevitably occurs as soon as the distance to the ball is low enough. These results suggest that subjects did not deviate from CBA, but rather waited for the bearing velocity to increase just enough to see the ball, and then counteracted the increasing bearing velocity once they started moving. Furthermore, most subjects did not actively try to increase the bearing velocity early in the trial (for example by moving on strongly curved paths), which would have enabled them to see the ball earlier. Although two of the participants did move sideways during the early phase of the trial when the ball was not visible, they walked in opposite directions, which does not suggest any conclusion about a common explanation for their behavior. Therefore, the general pattern of behavior in the *bearing velocity* condition can not be interpreted as evidence against the CBA strategy.

The third condition, in which the ball's contrast decreased as a function of the subject's distance to a specific path, yielded a much lower rate of successful catches than the other two conditions. This can possibly be attributed to the fact that the visibility of the ball depended only on the subject's behavior - in contrast to the *bearing velocity* condition, where the contrast was a function of the relative movement of the subject and the ball and thus the ball's movement alone could cause an increase in contrast. Subjects therefore had to actively depart from usual interceptive behavior in order to see the ball after leaving their initial position, which most participants failed to do. A few participants, however, found a way to more successfully catch balls in the *fixed path* condition, which involved walking towards the right side of the room, where the path was located. This is indicated by the mean trajectories, which were slanted towards the right side of the room for the more successful participants. None of these participants closely followed the fixed path, but rather departed from it and crossed it again later. Because the participants started on the fixed path, the ball was perfectly visible in the beginning of each trial. The ball contrast then decreased, as soon the subjects left the path, and increased again when the subjects approached the path again towards the end of the trials. This resulted in a higher success rate for subjects that employed this strategy compared to the alternative strategy of watching the ball for a longer time while standing still and then attempting blind interception, even though the latter was associated with a higher mean ball contrast. However, the behavior of the more successful subjects was not overall linked to considerably stronger deviations from CBA than in the *constant* contrast condition.

Finally, we simulated trials of an agent moving at a constant velocity in the range of the subject velocities observed in the experiment. The simulation resulted in almost perfectly constant bearing angles in all target conditions. While this result is not really surprising, it emphasizes that a constant bearing angle is a geometric relation that holds true for any agent that intercepts a target while walking at a constant speed along a linear trajectory. This serves as a possible explanation why the different behavior in the *fixed path* condition was not associated with clear deviations from CBA. While some of the subjects learned that walking towards the right side of the room enabled them to see the ball again, they still moved on more or less linear trajectories. This kept the bearing angle approximately constant, even if no visual information about the bearing angle was available to them while the ball was not visible.

Another thing to take away from the results presented in this study is that there was a lot of variability in the trajectories within and between subjects, indicated by the final interception locations, which vary heavily even in the *constant* contrast condition, and also by the trajectory plots for single subjects. This observation reveals that average trajectories across trials possibly fail to capture some properties of the individual trajectories. Based on this, we emphasize that the comparison of human data to any kind of model should be conducted on the trial level instead of on average trajectories.

4.1 Limitations of the present study

One of the major limitations of this study was due to the complications posed by the VR environment. Several participants reported that they were afraid of acting normally in the virtual environment because they were aware of the possibility of crashing into the walls of the actual room, which were not visible in the virtual room. Although they were informed that the experiment was designed in a way that allowed for every ball to be caught within the bounds of the room and that they would be warned by an auditory signal if they came too close to the walls, some participants walked really carefully. Because it is not clear whether this issue also affected participants that did not explicitly mention their discomfort, this could possibly severely limit the generalizability of the results to real environments. One way to address the problem is to display the walls in the VR environment, which, however, raises the question how the availability a fixed external reference frame given by a wall affects behavior in the interception task. The presence of the walls could, for instance, facilitate access to optical variables that depend on an external reference (e.g. the bearing angle) and therefore influence behavior if the control strategy employed by humans relies on such variables. This is a question that could be addressed in a future study. Another way to overcome the subjects' fear of the walls would be to introduce additional practice trials since the four practice trials in this study turned out not to be sufficient for some subjects to make them feel comfortable with the VR setup. For participants without prior experience with VR hardware, it could therefore be beneficial to perform a different task (such as navigating between stationary targets in the room) before starting the experiment. This could help them accustom themselves in the virtual environment and lose their fear of walking in a natural way without revealing too much about the possible target conditions in the actual experiment. Of course, performing a similar study in a larger room would also be an option. Although the tracking area in this experiment was comparable to similar experiments (e.g. Fajen & Warren, 2004; Fink et al., 2009; Sugar et al., 2006), the lab spaces in these studies were most probably larger, leaving a few meters as a buffer between the tracking area and the walls.

Besides the effect the limited room size had on the participants, it also implied substantial constraints for the experimental design. The balls had to be launched in a way that would enable interception without leading the participants too close towards the edges of the room. To prevent the participants from the danger of running into the walls, the speed and movement direction of the balls had to be chosen such that all of the balls could be caught near the middle of the room. This resulted in balls that were easy to catch even if they were not visible for a large part of a trial (like in the *bearing velocity* condition), as long as they were visible during the final part of the trial to allow for manual interception.

This experiment can therefore not answer the question how a ball contrast that varies based on the bearing velocity would affect behavior when current visual information plays a bigger role because the interception location is harder to predict. This could, for example, be achieved by introducing more variability in the ball positions and velocities or by using balls that move on a curved trajectory or change their speed. Under such circumstances, the catcher would possibly need to rely more strongly on current visual information and perhaps walk in ways that would enable better visibility of the ball. In this experiment, people had no incentive to deviate from running on a straight path, since they could catch the ball even without seeing it properly during the middle part of the trial. Another problem with the *bearing velocity* condition was the fact that the ball was not visible initially. In contrast to the author's expectations gained from previous test runs of the experiment, most participants did not start moving before the ball became visible on its own. Thus, they had substantially less time to catch it, which makes comparing behavior between the conditions harder. If the initial conditions were chosen such that the ball was visible in the beginning of the trial and only disappeared once a subject started moving according to the CBA strategy, this would have possibly allowed for more valid comparisons between the *bearing velocity* and the *constant* contrast conditions.

The low success rate in the *fixed path* condition was also problematic. Several subjects did not catch a single ball in some sub-conditions, which made averaging within subjects and comparisons between subjects difficult. Due to the low number of repetitions in this study (only 4 repetitions if the mirrored trials are treated as different conditions), it is not clear if humans are generally not able to adapt to the challenge posed by this contrast manipulation. Since at least some participants showed an increase in the success rate, it is not ruled out that additional trials would have allowed the subjects to develop a strategy to catch the balls in this condition.

4.2 Future directions

The study presented in this thesis, due to several methodological flaws, failed to provide a clear conclusion about whether humans can learn to deviate from the CBA strategy. Some aspects of the results are nevertheless worthy of further investigation. One thing that the trials in the *bearing velocity* and those of the more successful subjects in the *fixed path* condition have in common, is that the contrast changed in a way that allowed for an early and a late observation of the ball, which was invisible during the middle of the trial. Taken together, these results from both contrast manipulations suggest that continuous visibility of the target is not necessary to catch balls which move at a constant velocity. Instead, a short observation early in the trial can be enough, as long as the target becomes visible again later.

But how are the catcher's actions guided while the ball is not visible? In this phase, heuristics based on on-line visual information obviously break down. There are two possible answers to this question. Humans could either use a predictive model or a set of off-line heuristics. The model-based account states that the catcher constructs an internal model of the environment to predict the target's trajectory. Zhao and Warren (2015), on the other hand, argue in a recent review that a model-based control strategy is not supported by empirical evidence and that simple heuristics or mappings are more suitable to explain human behavior. As an example of such an off-line heuristic, a correlation between an optical variable (e.g. the rate of change in the visual angle of the target before it becomes invisible) and the time until a goal state is reached (e.g. the arrival of the target at some specified location) could be learned without relying on a sophisticated model that predicts future states of the environment. It is difficult to find a clear answer to this question because the trajectories produced by predictive strategies and heuristics might not even be distinguishable under most conditions and, as Zhao and Warren (2015) point out, formal descriptions of internal models as well as off-line heuristics are lacking. Future research should therefore concentrate on formalizing possible internal models and heuristics and experimentally test the conditions under which the predictions of these diverge.

4.2.1 Computational model

In order to address the question whether humans act according to an optimal control strategy based on an internal model, it is necessary to compare human behavior to the actions predicted by such a model. Belousov et al. (2016) have presented the first attempt at a computational model of human ball-catching behavior. While the model provides an explanation for several catching heuristics by showing that they are an optimal solution to a complex computational problem, it is based on a few simplifying assumptions. First, the uncertainty in the observations of the ball is modeled as Gaussian noise with a spherical covariance matrix. However, there are differences in the estimation of lateral and in-depth motion, which are not captured by a spherical covariance. The human visual system is more sensitive to lateral motion than to motion-in-depth. This results in a stronger influence of a prior that favors slow velocities on the in-depth component of a target's motion than on the lateral component (Welchman, Lam, & Bülthoff, 2008). A computational model of ball-catching should incorporate such differences in order to more closely capture the characteristics of the human visual system. Second, the cost function of the catching agent was chosen in a way that minimizes the distance between the predicted final positions of the ball and the agent while also minimizing the uncertainty as well the agent's effort at every time step. The weights of these three objectives were chosen by hand. It is not clear how exactly humans trade off maximizing the probability of a successful catch, minimizing uncertainty along the way, being energy efficient and possibly other costs involved in a motor control task. One possible way to obtain the intrinsic cost functions from observed optimal behavior is Inverse Reinforcement Learning (Ng & Russell, 2000). Future research could assess whether Inverse Reinforcement Learning algorithms can be applied to the problem of catching balls.

Furthermore, it would be interesting to test how an agent acting according to an optimal control strategy would behave under conditions like those in the present study (after addressing the issues discussed in Section 4.1). Would they deviate from known heuristics if adhering to these would make the ball hard to see? Would they walk along an uncommon path if that would increase the visibility of the ball? How would their trajectories compare to those of human subjects? In order to implement this, the ball contrast has to be incorporated into the observation function in a way that increases the visual uncertainty when the contrast decreases. An experiment like this could further the understanding of how humans cope with situations in which the commonly assumed heuristics can not be considered viable and, more importantly, help answer the question whether the catching heuristics are indeed optimal policies that result from a more general predictive model. The implementation of such a model, however, is beyond the scope of this thesis.

4.2.2 Predictive cues from optical variables

For an agent acting according to an on-line heuristic based only on current visual information, the availability of early visual information should not improve interception performance. In a recent study on manual interception of balls, de la Malla and Lopez-Moliner (2015), however, showed that availability of early vision improved the precision of the timing of interceptive actions. Balls were presented in three viewing conditions (early, late and full path) and always landed at the same location, thus posing only a timing problem. Early (predictive) and late (on-line) cues of time to contact (TTC) calculated from different optical variables were integrated in an optimal fashion similar to maximum likelihood estimation. Since the predictive cue was a simple estimate of TTC based on optical variables, this can not be considered evidence for sophisticated internal models. It can rather be interpreted as a kind of off-line heuristic that establishes a mapping from an optical variable to a variable that is of interest for the task. The results nevertheless show that prediction plays a role in interceptive behavior and lead to the question how the findings in a temporal manual interception task transfer to a spatiotemporal locomotor interception task like the one in the present study. Do humans extract reliable predictive cues from the early parts of the ball trajectory that enable them to guide their actions towards a successful catch once the ball becomes invisible? Our results suggest that humans can obtain enough information from a short early observation of a target that moves at a constant velocity to execute adequate interceptive actions when vision of the target is interrupted. In order to test which heuristics guide the actions during invisibility of the target, future research should examine which optical variables serve as predictive cues in spatiotemporal interception tasks. While cues of TTC have been extensively studied, less is known about spatial cues (see Zago, McIntyre, Senot, & Lacquaniti, 2009, for an overview). Once the relevant optical variables are specified, possible heuristics can be formalized as a relationship between the cues defined by these variables and the human behavior.

4.2.3 Fly balls

The findings presented in this study are limited to the interception of targets that move at a constant velocity parallel to the ground. An extension of the experimental design to fly balls could be valuable in testing the heuristics for catching fly balls. Because the trajectories of fly balls are harder to predict than those of balls with a constant velocity, this could also help with the problems mentioned in Section 4.1.

One idea for a contrast manipulation for fly balls would be to vary the ball's contrast such that a low velocity of the trajectory projection angle γ would lead to a low ball contrast. Since maintaining a linear optical trajectory (LOT) implies nulling the velocity of γ, this manipulation would make the ball harder to see when the catcher acts according to the LOT model. If such a manipulation elicits deviations from LOT, this could provide additional evidence that LOT is not the strategy that humans use to catch balls. Since OAC is possible without maintaining a LOT (and the other way around), manipulating the ball contrast in a way that affects only one of these strategies could help discriminating between these strategies. Conversely, one could vary the ball contrast as a function of the acceleration of the elevation angle α in order to test the OAC strategy. These manipulations could, on the one hand, contribute to identifying which of the different heuristics for catching fly balls is really used by humans. On the other hand, they could help to answer the question whether these heuristics are actually the mechanisms that guide human movement, or rather side effects of an optimal control strategy, which break down when adhering to them would increase uncertainty in the observations.

There is, however, one major problem in implementing contrast manipulations that depend on the velocities and especially the accelerations of angles in a virtual environment. These angles are obtained from noisy position data from a position tracking system. Numerically computing their time derivatives introduces additional noise, which can strongly affect the change in ball contrast. While the contrast manipulation based on the bearing velocity, that was used in this experiment, yielded sufficiently smooth results, this might break down when using the velocity of an angle that changes faster or the acceleration of an angle. Thus, a more precise tracking system with a higher update rate could be needed for these contrast manipulations.

4.3 Conclusion

The purpose of this study was to find out whether humans can learn to catch balls under visual conditions that make it hard to act according to the CBA heuristic and if this leads to deviations from CBA. One condition, in which a constant bearing angle was punished through a low ball contrast, elicited clear changes of the bearing angle over time, while participants still managed to catch most of the balls. These changes were, however, likely caused by flaws in the experimental design rather than by a strategy employed by the participants. Almost all subjects remained inactive as long as the bearing velocity was too low to see the ball and then counteracted the increasing bearing velocity. In the other condition, in which participants had to follow a specific path in order to see the balls, the success rates were significantly lower, indicating that most subjects did not develop a strategy to catch the balls. Only some participants found a way to catch balls in this condition, although their behavior was not associated with clear deviations from CBA.

Thus, we can not conclude that humans can learn to deviate from the CBA strategy. The results nevertheless allow for some insights into interceptive behavior under visual uncertainty. Short early vision of the ball combined with a late observation was sufficient for the subjects to catch the balls. This suggests that the interception of targets that move at a constant velocity is a rather easy task, for which permanent vision of the ball is not needed. But how are the catcher's actions guided during invisibility of the ball? This remains an open question. The data presented in this experiment does not allow a conclusion about whether humans use a sophisticated predictive model or some simple heuristic.

In order to shed light on this question, we suggest a few things that should be addressed by future research. First, the above-mentioned flaws in the experimental design of this study should be ironed out prior to repeating the experiment. In our opinion, the contrast manipulation from the *bearing velocity* condition suffered from these issues and could potentially bring new insights if repeated in an improved manner and applied to the problem of fly balls. Second, the computational model of ball catching (Belousov et al., 2016) should be extended to incorporate the ball contrast into the observation function. This would enable a comparison of the human data from an experiment like this to the trajectories produced by an optimal control agent. Third, possible heuristics, which guide actions when vision of the target is not available, should also be specified and formalized in order to allow for them to be experimentally tested.

These steps would help approach the question whether humans rely on a set of heuristics or plan their actions in an optimal fashion when intercepting moving objects in a more quantitative way, and thus contribute to the ongoing debate about whether complex tasks require complex solutions.

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Appendix

A Instruction text

Bälle fangen in Virtual Reality: Anweisungen

Für dieses Experiment betreten Sie eine virtuelle Umgebung, in der Sie sich frei bewegen können. Dazu werden Sie ein sogenanntes Head-Mounted Display tragen, das über einen Laptop in Ihrem Rucksack betrieben wird. Zudem werden während des Versuchs Ihre Augenbewegungen aufgezeichnet.

Sie werden einen Baseballhandschuh anziehen, mit dessen Hilfe Sie virtuelle Bälle fangen können. Ihre Aufgabe besteht darin, so zu laufen, dass Sie möglichst viele Bälle erfolgreich fangen! Die Bälle können sich dabei in verschiedene Richtungen und mit verschiedenen Geschwindigkeiten bewegen.

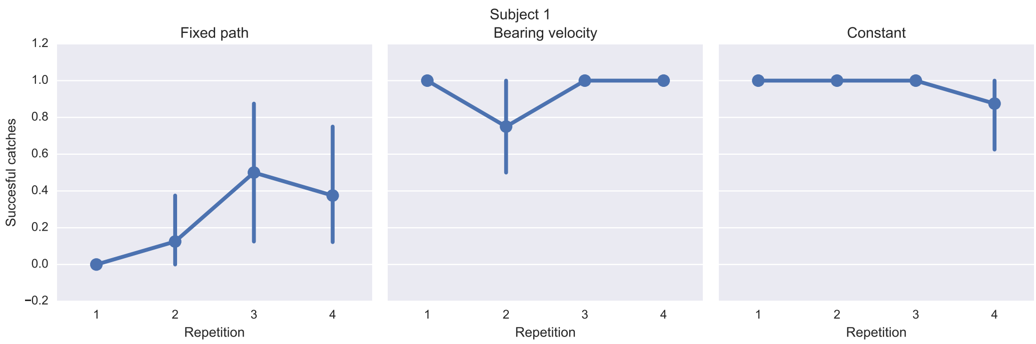
Außerdem gibt es verschiedene Sorten von Bällen. Einige dieser Bälle werden Ihnen zunächst äußerst merkwürdig vorkommen, da sich ihr Aussehen auf ungewohnte Weise verändert. Sie können dennoch lernen, diese Bälle erfolgreich zu fangen, indem Sie sich auf kreative Art und Weise bewegen.

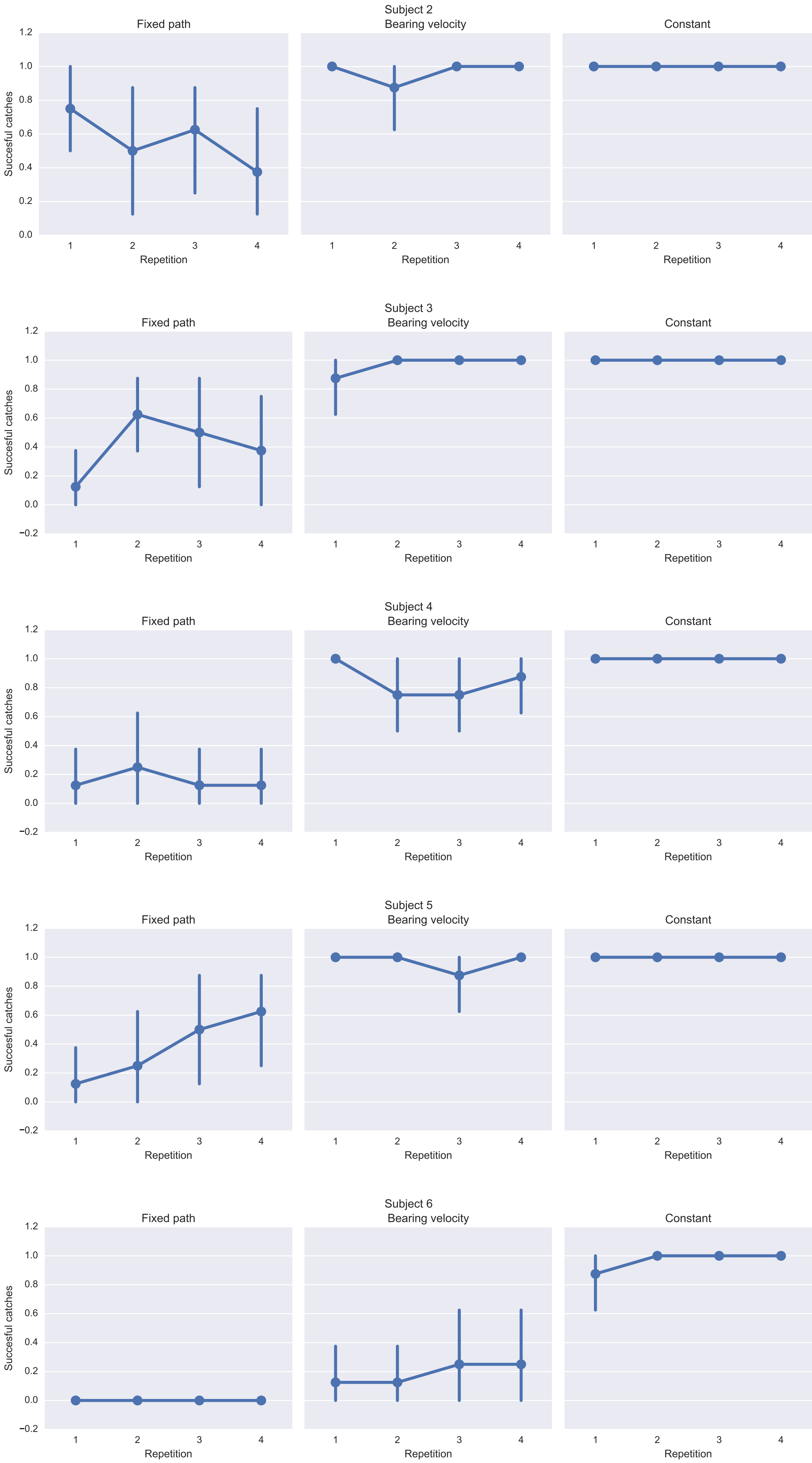
Das Experiment besteht aus mehreren Blöcken, in denen jeweils eine Sorte von Bällen auftritt. Das Ende jedes Blocks wird Ihnen durch eine Nachricht auf dem Display angezeigt. Sie können jederzeit eine Pause einlegen - wenden Sie sich dazu einfach an den Versuchsleiter.

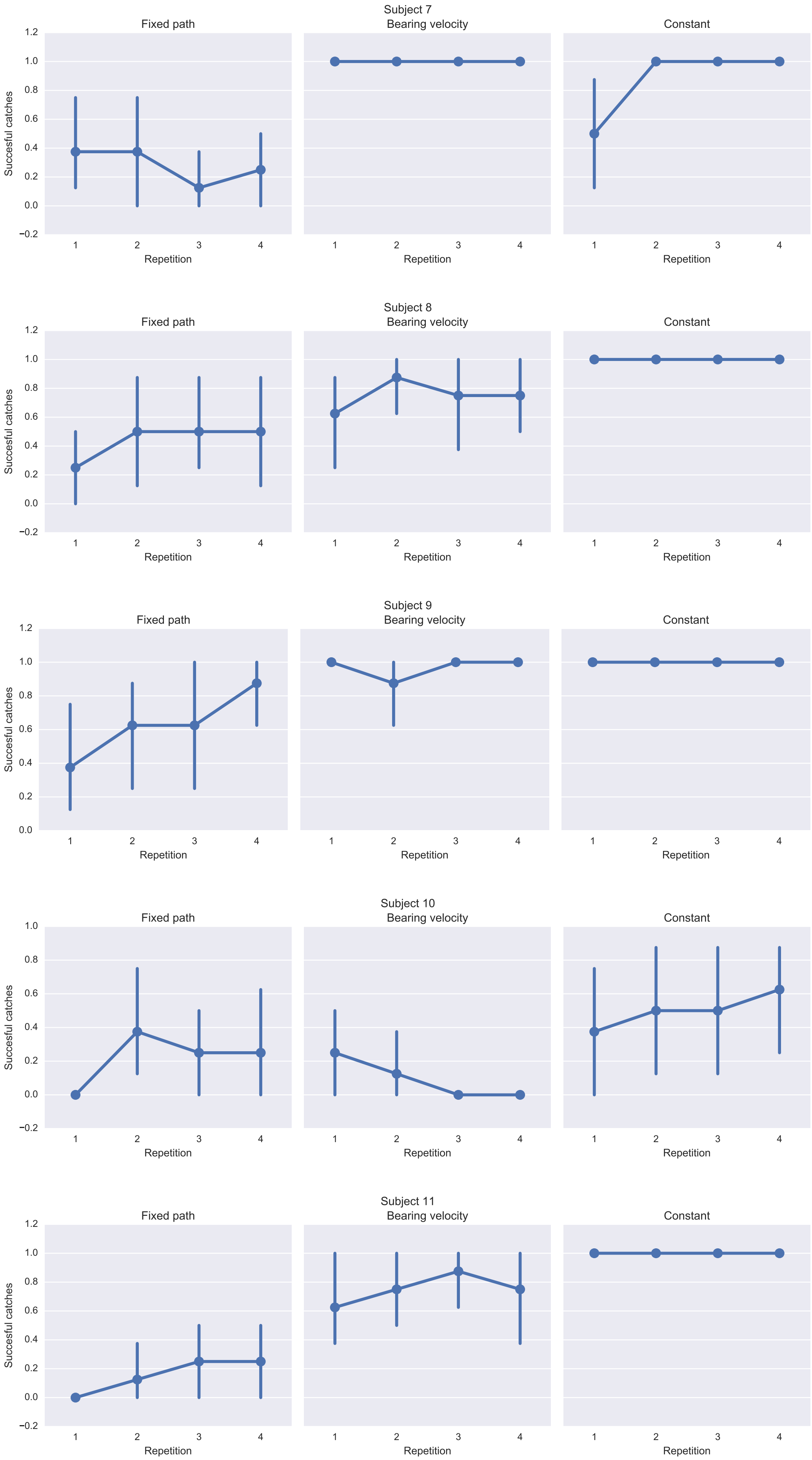
Die ersten 4 Bälle sind Training und dafür gedacht, Sie mit dem Ablauf vertraut zu machen.

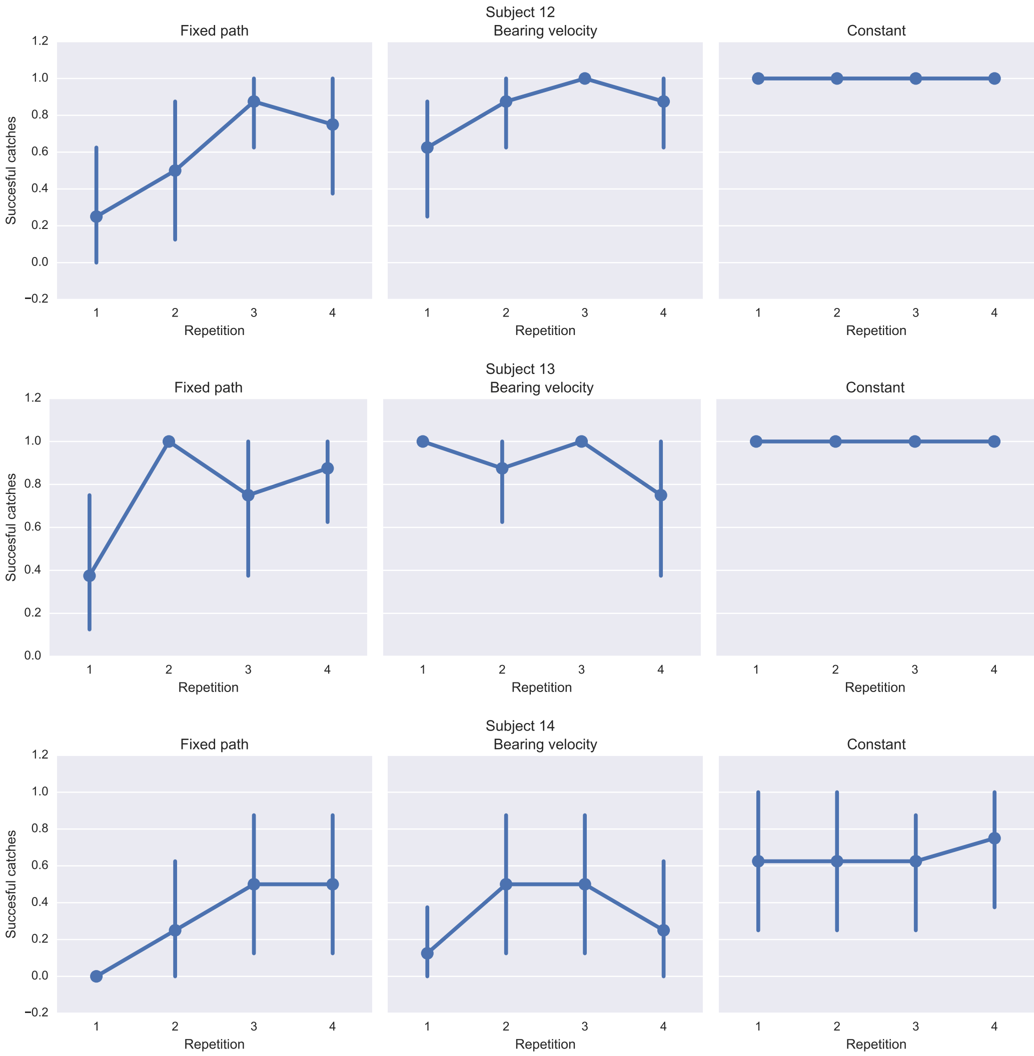
Wenn noch Fragen offen sind, wenden Sie sich bitte an den Versuchsleiter.

B Interception success per subject




Subject 2
Fixed path
Bearing velocity
Constant
Succesful catches
Repetition
Subject 3
Fixed path
Bearing velocity
Constant
Succesful catches
Repetition
Subject 4
Fixed path
Bearing velocity
Constant
Succesful catches
Repetition
Subject 5
Fixed path
Bearing velocity
Constant
Succesful catches
Repetition
Subject 6
Fixed path
Bearing velocity
Constant
Succesful catches
Repetition


Subject 7
Fixed path
Bearing velocity
Constant
Succesful catches
Repetition
Subject 8
Fixed path
Bearing velocity
Constant
Succesful catches
Repetition
Subject 9
Fixed path
Bearing velocity
Constant
Succesful catches
Repetition
Subject 10
Fixed path
Bearing velocity
Constant
Succesful catches
Repetition
Subject 11
Fixed path
Bearing velocity
Constant
Succesful catches
Repetition



C Plots

Plots that include trajectories, bearing angles and velocity profiles as well as plots of bearing velocities and ball contrast for every subject and every condition can be obtained from the ’plots’ directory on the accompanying DVD.

D Experiment software

The code used to perform the experiment can be found in the ’experiment_code’ directory on the accompanying DVD. In order to run the code, some additional software is needed. Beside WorldViz Vizard 5.6 or higher, the following Python packages need to be installed for Vizard’s Python environment:

- numpy
- pandas
- PyODE
- ConfigObj

In addition to this, an up-to-date version of the Oculus Rift Runtime has to be installed, as well as version 1.5 of the SMI Eye Tracking HMD Upgrade software.

E Recorded data

The recorded data of all subjects are included as *data.zip* on the accompanying DVD. In order to facilitate recreation of the analysis, the data are already preprocessed using the *preprocess_data.ipynb* notebook (see Appendix F). The file *all_data.csv* contains data from all subjects and *all_data_collapsed.csv* contains the same data, but with mirrored trials flipped along the z axis.

F Data analysis notebooks

The Jupyter notebooks and Python scripts used for the analysis can also be found on the DVD (in the 'data_analysis' directory). Python 3.6 with the following packages is needed to recreate the analysis:

- numpy 1.11.3
- scipy 0.18.1
- pandas 0.19.2
- matplotlib 2.0.0
- seaborn 0.7.1

An easy way to install all these packages at once is the Anaconda distribution, which can be downloaded at https://www.continuum.io/downloads. Table A1 indicates in which notebooks to find the code to reproduce the results presented in this thesis.

Table A1: Data analysis notebooks

Notebook	Contents	Sections
preprocess_data.ipynb	Read and preprocess data	
report.ipynb	Success rates, trial duration, subject speed, mean ball contrast	3.1, 3.2
interception_location.ipynb	Final locations	3.4
gaze_angles.ipynb	Bearing, heading, gaze and view angles, saccade detection	2.5, 3.3
trajectory_bearing.ipynb	Trajectory, bearing angle and velocity plots	3.5
bearing_velocity.ipynb	Bearing velocities over time	3.5
ball_contrast.ipynb	Ball contrast over time	3.6
simulate_trajectories.ipynb	Simulated trajectories	3.7

Additional functions for reading data as well as computing the subjects' speed and heading angle are contained in *read_data.py*. All other functions used in the notebooks can be found in *data_utils.py*. The ANOVAs presented in this thesis were conducted using R and can be found in *ANOVAs.R*.