

# Visuomotor predictors of batting performance in baseball players

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**Hitting a baseball, one of the most difficult skills in all of sports, requires complex hand-eye coordination, but its link with basic visuomotor capabilities remains largely unknown. Here we examined basic visuomotor skills of baseball players and demographically matched nonathletes by measuring their ocular-tracking and manual-control performance. We further investigated how these two capabilities relate to batting performance in baseball players. Compared to nonathletes, baseball players showed better ocular-tracking and manual-control capabilities, which remain unchanged with increasing baseball experience. Both, however, become more correlated with batting accuracy with increasing experience. Ocular-tracking performance is predictive of batting skill, accounting for  $\geq 70\%$  of the variance in batting performance across players with  $\geq 10$  years of experience. A simple linear additive-noise cascade model with shared front-end visual noise that limits batting performance can explain many of our results. Our findings show that fundamental visuomotor capabilities can predict the complex, learned skill of baseball batting.**

at nearly 100 mph, often along a curved trajectory. This amazing feat leads to the question of what elemental skills are critical to hit a pitch successfully. It has been proposed that these elemental skills include (a) encoding visual motion signal to form the percept of pitch trajectory, (b) making a decision about whether to swing, and (c) coordinating multiple motor systems to drive and adjust the swing (Adair, 1990; Bahill & LaRitz, 1984; Williams & Underwood, 1970). Because these skills are largely visuomotor, the questions arise: Do baseball players have better basic visuomotor capabilities, compared to nonathletes, and how are these capabilities related to their batting performance?

Previous behavioral studies on baseball players have studied their low-level visual function (e.g., acuity, stereoacuity, and contrast sensitivity; Laby et al., 1996; Molia, Rubin, & Kohn, 1998; Uchida, Kudoh, Murakami, Honda, & Kitazawa, 2012), the type of visual or perceptual information needed to successfully hit (Bahill & LaRitz, 1984; Gray, 2002a; Higuchi, Morohoshi, Nagami, Nakata, & Kanosue, 2013; Ranganathan & Carlton, 2007) or catch a ball (Fink, Foo, & Warren, 2009; McBeath, Shaffer, & Kaiser, 1995; McLeod & Dienes, 1996; Shaffer & McBeath, 2002), their cognitive processing (Gray, 2002b), and their eye movements outside the context of batting (Fooker & Spering, 2019; Fooker, Yeo, Pai, & Spering, 2016). Previous studies, however, have not comprehensively characterized the full range of basic visuomotor capabilities of baseball players and, more important,

## Introduction

Hitting a baseball is considered “one of the most difficult skills in sports” (DeRenne, 2007). This is because baseball players have less than 500 ms to plan and execute their swing to hit a pitch coming at them

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have not examined how these capabilities could be related to batting performance. To fill this research gap, in the current study, we used two methods that we previously developed to measure ocular-tracking and manual-control performance to assess baseball players on the Hong Kong National Baseball Team and demographically matched nonathletes. In the ocular-tracking task, participants were asked to follow an unpredictably moving target with their eyes (Krukowski & Stone, 2005; Liston & Stone, 2014). This task is designed to assess dynamic aspects of vision, smooth pursuit tracking, and the coordination of pursuit with saccades. In the manual-control task, participants were asked to use a joystick to control a randomly moving target (Li, Sweet, & Stone, 2005). This task mimics the visuomotor control component of lane keeping (see Li, Chen, & Chen, 2016) and allows us to evaluate many aspects of closed-loop visuomotor control such as overall performance error, response gain, and response delay.

We expected that, due to the highly elite nature of baseball players selected by the team, they would show better ocular-tracking and manual-control capabilities compared with nonathletes. However, basic visuomotor tasks likely reach asymptotic performance by early adulthood with just everyday experience, whereas baseball batting requires years of specialized training and practice before reaching its peak. We therefore expected that ocular-tracking and manual-control performance would not change with experience in playing baseball, but batting performance would. Furthermore, if basic visuomotor capabilities (such as ocular tracking and manual control) and sophisticated, learned visuomotor skills (such as baseball batting) share fixed and rate-limiting noise in visual motion processing, we anticipated that either ocular-tracking or manual-control performance would predict batting performance and that their power of prediction could change with baseball experience. The primary goal of this study was to determine effective basic visuomotor predictors of batting performance in baseball players.

## Methods

### Participants

Forty-four baseball players on the Hong Kong Baseball National Team (17 males, 27 females) in the age range of 18 to 45 years (mean  $\pm$  *SD*: 27  $\pm$  8 years) with baseball experience in the range of 3 to 30 years (mean  $\pm$  *SD*: 11  $\pm$  6 years) participated in this study. Although none of them were professional baseball players, all had competition experience in major international baseball contests such as the Hong Kong Baseball Open, the Phoenix Cup Hong Kong International Women's Baseball Tournament, and/or

the Women's Baseball World Cup. Many also played softball before starting playing baseball and joining the National Team. Based on their field positions in major baseball contests, there were 16 infielders (9 males, 7 females), 12 outfielders (3 males, 9 females), 12 pitchers (3 males, 9 females), and 4 catchers (2 males, 2 females) in our baseball player participant group. According to the World Baseball Softball Confederation, the Hong Kong men's national baseball team was ranked 30th out of 85 nations and the Hong Kong women's team was ranked 10th out of 20 nations in 2019.

Forty-seven demographically matched healthy nonathletes (20 males, 27 females) in the age range of 18 to 39 years (mean  $\pm$  *SD*: 24  $\pm$  6 years) participated in the experiment as the control group. All were staff or students at the University of Hong Kong and reported having no previous competitive ball-sports experience.

All participants were right-handed and had normal or corrected-to-normal vision. No participant wore corrective lenses, and only two nonathlete participants wore glasses. All participants were naive to the purpose of the study and provided informed consent in accordance with guidelines from the Human Research Ethics Committee of the University of Hong Kong. All 44 baseball players completed the ocular-tracking task. One female player (pitcher) did not participate in the manual-control task, leaving 43 baseball players who completed the manual-control task. All 47 nonathletes completed the manual-control task. Three female and two male nonathletes could not generate valid data for the ocular-tracking task, leaving 42 nonathletes who completed the ocular-tracking task. The ocular-tracking and manual-control tasks were tested on the same day, and the testing order was counterbalanced across participants. Among the 44 baseball players, 23 female players in the age range of 18 to 41 years (mean  $\pm$  *SD*: 28  $\pm$  8 years) with baseball experience in the range of 3 to 18 years (mean  $\pm$  *SD*: 9  $\pm$  4 years) volunteered to participate in the batting performance test on a different day.

The sample size of this study was chosen intuitively based on our extensive experience in research on visuomotor control and was at the upper end of the range of participants commonly run in such experiments.

### Ocular-tracking task

#### *Stimuli and apparatus*

The ocular-tracking task has been described previously (Liston & Stone, 2014; Stone, Tyson, Cravalho, Feick, & Flynn-Evans, 2019). It was based on the classic Rashbass (1961) step-ramp paradigm modified to accommodate a full sampling of the polar angles using 180 trials with each trial along every even angle around the clock. On each trial, a red dot target

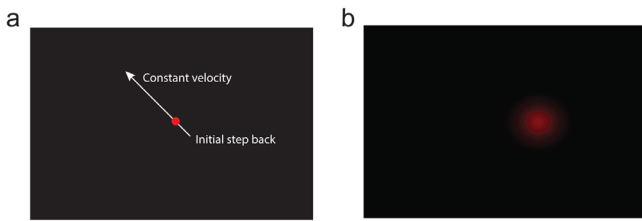


Figure 1. Experimental displays. (a) An illustration of the display for the ocular-tracking task. On each trial, the red dot made an initial step off the screen center. It then moved back through its initial location at a constant velocity until it disappeared from the screen edge. The size of the red dot is scaled up for illustration purposes. (b) An illustration of the display for the manual-control task. The blurred red target moved along the horizontal axis in the middle of the screen, and this case illustrates a rightward initial target position error from the center of the screen.

( $0.64^\circ$ ;  $8.8 \text{ cd/m}^2$ ) was displayed in the center of a black background ( $2.2 \text{ cd/m}^2$ ) on a computer screen ( $39^\circ\text{H} \times 30^\circ\text{V}$ ). Participants were asked to fixate the central target and press a mouse button to trigger the start of each trial. After a random time delay drawn from a truncated exponential distribution (mean: 700 ms; minimum: 200 ms; maximum: 5,000 ms), the target would jump  $3.2^\circ$  to  $4.8^\circ$  away from the fixation point and immediately move back at a constant speed toward the center of the screen and then onward for a random amount of time from 700 to 1,000 ms before disappearing (see Figure 1a). To minimize the likelihood of an initial catch-up saccade, the target always crossed the center of the screen at 200 ms after its motion onset. Both the target speed and moving direction were randomly sampled from a range (speed range:  $16\text{--}24^\circ/\text{s}$ ; direction range:  $0\text{--}358^\circ$  in  $2^\circ$  increment without replacement) to minimize expectation effects. Participants were instructed to keep their eyes on the target in the center without blinking once they initiated the trial and then to follow it as best as they could once it started moving until it disappeared.

The visual stimuli were presented on a 21-in. CRT monitor ( $1,280 \times 960$  pixels; Mitsubishi Diamond Pro 2070 SB, Tokyo, Japan) at 100 Hz. Participants' eye movements were recorded by an infrared camera-based eye tracker (Eyelink 1000; SR Research, Ottawa, Canada) at 250 Hz. Participants were seated in a dark room with their head stabilized by a chin cup and a forehead bar at a viewing distance of 56.5 cm. Before the start of the ocular-tracking task, all participants went through a 13-point calibration and validation procedure provided by the eye tracker that had them fixate nine locations on a  $3 \times 3$  Cartesian grid and four locations in the center of each of the four quadrants. If the participant took a brief rest during the ocular-tracking task, the calibration and

validation procedure would be repeated before they resumed tracking again. Most participants took two rests in between tracking. The mean gaze error averaged across all the calibration and validation procedures each participant went through was  $0.81 \pm 0.04^\circ$  (mean  $\pm$  SE) for the baseball players and  $0.68 \pm 0.03^\circ$  for the nonathletes. The ocular-tracking task took less than 30 min to finish.

### Data analysis

We recorded the time series of the eye and target (i.e., red spot) positions. Prior to any analysis, we detected and segregated saccade eye movements using a method that has been validated in our previous studies (Liston, Krukowski, & Stone, 2013; Niehorster, Siu, & Li, 2015). We modified this method to apply a biphasic saccade template appropriate for the high spatiotemporal fidelity of our 250-Hz eye tracker. As such, we were able to reliably detect and remove saccades down to approximately one eighth of a degree in amplitude.

Our oculometric assessment method has been described previously (Liston & Stone, 2014; Stone et al., 2019). In a nutshell, we computed 12 different oculometric measures to evaluate four different aspects of participants' ocular-tracking performance:

1. Pursuit initiation as measured by *latency* (the median across trials of the time between target motion onset and the initiation of smooth pursuit eye movements) and *open-loop acceleration* (the median across trials of the mean radial acceleration along the target direction of smooth pursuit in the 100-ms interval immediately following pursuit onset).
2. Steady-state tracking as measured by *steady-state gain* (the median across trials of the mean speed of smooth pursuit in the steady-state tracking interval 400 to 700 ms after motion onset, projected along the direction of target motion and divided by the target speed), *proportion smooth* (the median across trials of the proportion of time that tracking within the steady-state tracking interval was smooth pursuit, as a metric of how much pursuit is contributing to steady-state tracking), *saccadic rate* (the total number of both forward and backward catch-up saccades made in the 400- to 700-ms period of steady-state tracking divided by the total steady-state tracking time, i.e., 300 ms), *saccadic amplitude* (the median amplitude of the forward catch-up saccades occurring in the steady-state tracking interval with forward saccades classified as within  $180^\circ$  of the direction of target motion), and *saccadic dispersion* (the standard deviation of the distribution of directions across forward catch-up saccades).

3. Direction tuning as measured by *direction noise* and *direction asymmetry and anisotropy*. Direction noise is the average across trials of the local standard deviations taken across the measured pursuit directions at a given direction and its two nearest neighbor directions corrected for the 2° expected differences. *Direction asymmetry and anisotropy* refer to vertical-horizontal asymmetry and oblique-cardinal anisotropy, respectively, which are the best-fitting first and second polar harmonic modulations of the direction gain (i.e., the local linear regression slope of the pursuit- versus target-direction curve within a 30° window; see details in [Krukowski & Stone, 2005](#), and [Liston & Stone, 2014](#)).
4. Speed tuning as measured by *speed noise* (the standard deviation across trials of the difference between the actual radial pursuit speed and the best linear regression estimate for a given target speed divided by the mean target speed) and *speed responsiveness* (the best-fitting linear regression slope of the mean radial pursuit speed vs. target speed). These two measures capture how well pursuit can discriminate between small differences in target speed as opposed to how *effective* the pursuit response is in general, which is captured by steady-state gain.

To ensure the quality of the data, we excluded trials from the analysis if blinks or other artifacts obscured that part of a trial used for the computation of specific oculometric measurements, but this occurred relatively rarely. Specifically, for the baseball players, on average,  $152 \pm 4$  (mean  $\pm$  SE) out of 180 trials were used for the pursuit-initiation and direction-tuning analysis, and  $168 \pm 3$  out of 180 trials were used for the steady-state tracking and speed-tuning analysis. For the nonathletes, on average,  $136 \pm 4$  out of 180 trials were used for the pursuit initiation and direction-tuning analysis, and  $163 \pm 3$  out of 180 trials were used for the steady-state tracking and speed-tuning analysis.

To characterize the baseball experience-related characteristics present in the ocular-tracking performance, we combined all 12 oculometric measures to compute an ocular-tracking performance index for each baseball player and nonathlete. The index value indicates how closely an individual participant’s ocular-tracking performance matches the average performance of the baseball players. Specifically, like the procedure in [Liston, Wong, and Stone \(2017\)](#), we first used the data of the nonathletes to define a normative standard and calculated its median ( $M$ ) and standard deviation ( $\sigma$ ):

$$M = Control_{50th} \quad \text{and}$$

$$\sigma = \frac{Control_{75th} - Control_{25th}}{2\phi^{-1}(0.75)}, \quad (1)$$

in which  $\phi^{-1}$  is the inverse of the normal cumulative distribution function. We then converted each raw oculometric measure into a  $Z$  value metric ( $\omega$ ) relative to the normative standard for each baseball player ( $\omega_{baseball}$ ) and nonathlete ( $\omega_{control}$ ):

$$\omega_{Baseball} = \frac{Baseball\ Raw - M}{\sigma} \quad \text{and}$$

$$\omega_{control} = \frac{Control\ Raw - M}{\sigma}. \quad (2)$$

This allowed us to construct a 12-element normalized oculometric vector for each baseball player (*Baseball  $\omega_i$* ) and nonathlete (*Control  $\omega_i$* ):

$$Baseball\ \omega_i = \begin{bmatrix} \omega_{Baseball\_latency} \\ \omega_{Baseball\_open-loop\ acceleration} \\ \omega_{Baseball\_steady-state\ gain} \\ \omega_{Baseball\_proportion\ smooth} \\ \omega_{Baseball\_saccade\ rate} \\ \omega_{Baseball\_saccade\ amplitude} \\ \omega_{Baseball\_saccde\ dispersion} \\ \omega_{Baseball\_direction\ noise} \\ \omega_{Baseball\_direction\ asymmetry} \\ \omega_{Baseball\_direction\ anisotropy} \\ \omega_{Baseball\_speed\ noise} \\ \omega_{Baseball\_speed\ responsiveness} \end{bmatrix}$$

and

$$Control\ \omega_i = \begin{bmatrix} \omega_{Control\_latency} \\ \omega_{Control\_open-loop\ acceleration} \\ \omega_{Control\_steady-state\ gain} \\ \omega_{Control\_proportion\ smooth} \\ \omega_{Control\_saccade\ rate} \\ \omega_{Control\_saccade\ amplitude} \\ \omega_{Control\_saccde\ dispersion} \\ \omega_{Control\_direction\ noise} \\ \omega_{Control\_direction\ asymmetry} \\ \omega_{Control\_direction\ anisotropy} \\ \omega_{Control\_speed\ noise} \\ \omega_{Control\_speed\ responsiveness} \end{bmatrix}.$$

To characterize baseball experience-related oculometric signs, we averaged the *Baseball  $\omega_i$*  vectors across our baseball player population to yield a baseball vector (*Baseball vector*):

$$Baseball\ vector = \sum_{i=1}^n \frac{Baseball\ \omega_i}{N_{Baseball}}, \quad (3)$$

where  $N_{Baseball}$  is the number of the baseball players. Because the *Baseball  $\omega_i$*  vectors are “normalized,” each element of the *Baseball vector* gives the distance (in  $z$  values) between the average baseball player participant and the average of the control population for a specific oculometric measure, and the larger



distances weight the oculometric measures with higher discrimination power. To quantify the scalar magnitude of ocular-tracking performance along the *Baseball vector*, we took the dot product between an individual's 12-element normalized oculometric vector (*Baseball  $\omega_i$*  or *Control  $\omega_i$* ) and the *Baseball vector* to yield a projection-based scalar metric (i.e., ocular-tracking performance index):

$$Index_{Baseball} = \frac{Baseball \ \omega_i \cdot (Baseball \ vector)}{Scaling \ Factor}$$

and

$$Index_{Control} = \frac{Control \ \omega_i \cdot (Baseball \ vector)}{Scaling \ Factor}, \quad (4)$$

with

$$Scaling \ factor = \|\text{CHOL}(\text{COV}(\text{Control } \omega) \cdot \text{Baseball } vector')\|, \quad (5)$$

where *Control  $\omega$*  is the matrix containing all oculometric vectors in the control population of nonathletes, COV is the covariance matrix, and CHOL is the Cholesky decomposition. Applying the Cholesky decomposition of the covariance matrix of *Control  $\omega$*  to the *Baseball vector* produces a sample baseball player vector with the covariance properties of the 12 oculometric measures in the control population. *Scaling factor* in the denominator thus normalizes the ocular-tracking performance index by taking the magnitude of the correlation between oculometric measures into consideration.

## Manual-control task

### Stimuli and apparatus

We used the closed-loop compensatory manual-control task as described in our previous studies (Li et al., 2005, 2016) to measure participants' manual-control performance. On each trial, a red round Gaussian-blurred target ( $\sigma$ : 3.1°; peak luminance: 2 cd/m<sup>2</sup>) was displayed on a uniform black background (0.14 cd/m<sup>2</sup>) on a rear projected large screen (110°H × 94°V) at 60 Hz (see Figure 1b). Its horizontal position was updated by a perturbation function  $u$  consisting of the sum of seven harmonically unrelated sinusoids, given as:

$$u(t) = D \sum_{i=1}^7 a_i \sin(2\pi f_i t + \rho_i), \quad (6)$$

where  $a_i$  represents the amplitude and  $f_i$  represents the frequency of the  $i$ th sine component (see Table 1).

Sinusoid ( $i$ )	$a$	$f$ (Hz)
1	2	0.10
2	2	0.14
3	2	0.24
4	0.2	0.41
5	0.2	0.74
6	0.2	1.28
7	0.2	2.19

Table 1. Amplitude ( $a$ ) and frequency ( $f$ ) for each of the seven harmonically unrelated sinusoids in the input position perturbation function  $u$ .

$\rho_i$  is a random phase offset drawn from  $-\pi$  to  $\pi$  on each trial.  $D$  is the disturbance gain, which was set to 8.1° and led to an average uncorrected perturbation speed of 25.1°/s (peak: 95.7°/s). This sum-of-sinusoids perturbation series made the target movement appear random and allowed for a frequency-based analysis of the control response.

At the beginning of each trial, the target appeared at the center of the screen and began moving when participants pulled the trigger of a high-precision joystick (Flybox; B&G Systems, Palo Alto, CA, USA). Participants were asked to smoothly move the joystick left and right to control the horizontal movement of the target to keep it stationary and as close to the center of the screen as possible. Initially, the target moved according to the sum-of-sinusoids perturbation, but as participants moved the joystick, the target position was affected by both the input perturbation and participants' joystick movement. We used acceleration controller dynamics for the joystick in which the joystick displacement (sampled at 60 Hz) was proportional to the acceleration of the target movement on the screen. The maximum displacement of the joystick corresponded to a peak target movement acceleration of 81.29°/s<sup>2</sup>.

Participants were seated in a light-excluded booth and viewed the display with their head stabilized by a chinrest at a viewing distance of 56.5 cm. Participants' cyclopean eye (i.e., their straight ahead) was aligned with the center of the screen before the data collection. Participants were given two practice trials to get familiar with the task and then completed six experimental trials in a single session. The duration of each trial was 95 s, and thus the manual-control task lasted about 20 min.

### Data analysis

We recorded the time series of the target position error, the joystick control output, and the input position perturbation. We skipped the data in the first 5 s out of each 95-s trial to avoid analyzing the initial transient response. We then computed three different measures as described in Li et al. (2005) to evaluate three different

aspects of participants' manual-control performance: (a) overall control performance as measured by the *root mean square* (RMS) of the time series of the target position error relative to the center of the screen, (b) control response amplitude and (c) delay, as measured by *gain* and *phase lag* from the frequency response (Bode) analyses on the recorded time-series data. Specifically, we performed Fourier transform of the time series of both the joystick control output (in percentage of maximum displacement) and the target position error (in degrees of visual angle or deg). We computed the control response amplitude (i.e., gain in percentage of max/deg) by taking the ratio of the Fourier coefficients of the joystick displacement and the target position error at each perturbation frequency, and the response delay (i.e., phase lag in degrees of sinusoidal phase or °) by taking the phase difference between the Fourier components of the joystick displacement and the target position error at each perturbation frequency.

To characterize the baseball-related characteristics present in the manual-control performance, we combined all three manual-control measures to compute a manual-control performance index for each baseball player and nonathlete. The index value indicates how closely an individual participant's manual-control performance matches the average performance of the baseball players. The computation procedure for the manual-control performance index is the same as for the ocular-tracking performance index described above (see Ocular-tracking task), except that we constructed a three-element normalized manual-control vector for each baseball player (*Baseball  $\omega_i$* ) and nonathlete (*Control  $\omega_i$* ):

$$\text{Baseball } \omega_i = \begin{bmatrix} \omega_{\text{Baseball\_RMS error}} \\ \omega_{\text{Baseball\_gain}} \\ \omega_{\text{Baseball\_phase lag}} \end{bmatrix}$$

and

$$\text{Control } \omega_i = \begin{bmatrix} \omega_{\text{Control\_RMS error}} \\ \omega_{\text{Control\_gain}} \\ \omega_{\text{Control\_phase lag}} \end{bmatrix}.$$

## Batting performance test

To measure the baseball players' batting capability in response to a known stimulus set, we used a three-wheel pitching machine (BMH33A; Nippon ZETT, Osaka, Japan) for the batting performance test. We tested six combinations of pitching speeds and trajectories (80 kph straight, 100 kph straight, 60 kph left/right curved, and 80 kph left/right curved) five times in a randomized order. In total, 30 balls were launched from the pitching machine at the height of 1.6 m and the distance of 18 m

away from the home plate. After sufficient warm-up and practice, each baseball player participant completed 30 swings to the 30 pitches, and the batting accuracy (i.e., hit or not) was evaluated by the head coach of the Hong Kong National Baseball Team for each pitch to allow us to compute the *hit rate* (total number of hits divided by 30). Due to the tight training schedule, participants were tested on two to three pitches per week, and the entire test lasted about 3 months.

## Results

### Ocular-tracking performance

Figure 2 plots the summary of the 12 different oculometrics measures for a typical baseball player (Figure 2a) and a nonathlete (Figure 2b). For the measurements of pursuit initiation and steady-state tracking shown in the histograms in the left column, the baseball player showed superior ocular-tracking performance compared with the nonathlete, as demonstrated by shorter latency, larger open-loop acceleration, larger steady-state gain and proportion smooth, and smaller catch-up saccade rate, amplitude, and dispersion. For the measurements of direction-tuning and speed-tuning shown in the scatterplots in the right column, the baseball player also showed superior ocular-tracking performance compared with the nonathlete, as demonstrated by smaller direction noise, smaller direction asymmetry and anisotropy, smaller speed noise, and higher speed responsiveness.

Figure 3 plots the histograms of the 12 oculometric measures for the 44 baseball players and the 42 nonathletes who completed the ocular-tracking task. Independent-samples *t* tests showed that the baseball players were superior to the nonathletes in all four aspects of ocular-tracking performance, as indicated by 8 out of 12 oculometric measures: shorter latency ( $t(84) = 2.84$ ,  $p = 0.0056$ , Cohen's  $d = 0.61$ ), larger open-loop acceleration that reached borderline significance ( $t(84) = 1.98$ ,  $p = 0.051$ , Cohen's  $d = 0.43$ ), larger steady-state gain ( $t(84) = 4.12$ ,  $p < 0.001$ , Cohen's  $d = 0.89$ ), smaller catch-up saccade amplitude ( $t(84) = 2.98$ ,  $p = 0.0038$ , Cohen's  $d = 0.64$ ) and dispersion ( $t(84) = 2.78$ ,  $p = 0.0068$ , Cohen's  $d = 0.60$ ), smaller direction noise ( $t(84) = 3.48$ ,  $p < 0.001$ , Cohen's  $d = 0.75$ ) and vertical-horizontal asymmetry ( $t(84) = 2.49$ ,  $p = 0.015$ , Cohen's  $d = 0.54$ ), and larger speed responsiveness ( $t(84) = 2.50$ ,  $p = 0.014$ , Cohen's  $d = 0.54$ ). In summary, despite considerable within-group variance observed for each oculometric measure, the baseball players systematically showed overall better ocular-tracking performance than did the demographically matched nonathletes across most (but not all) metrics.

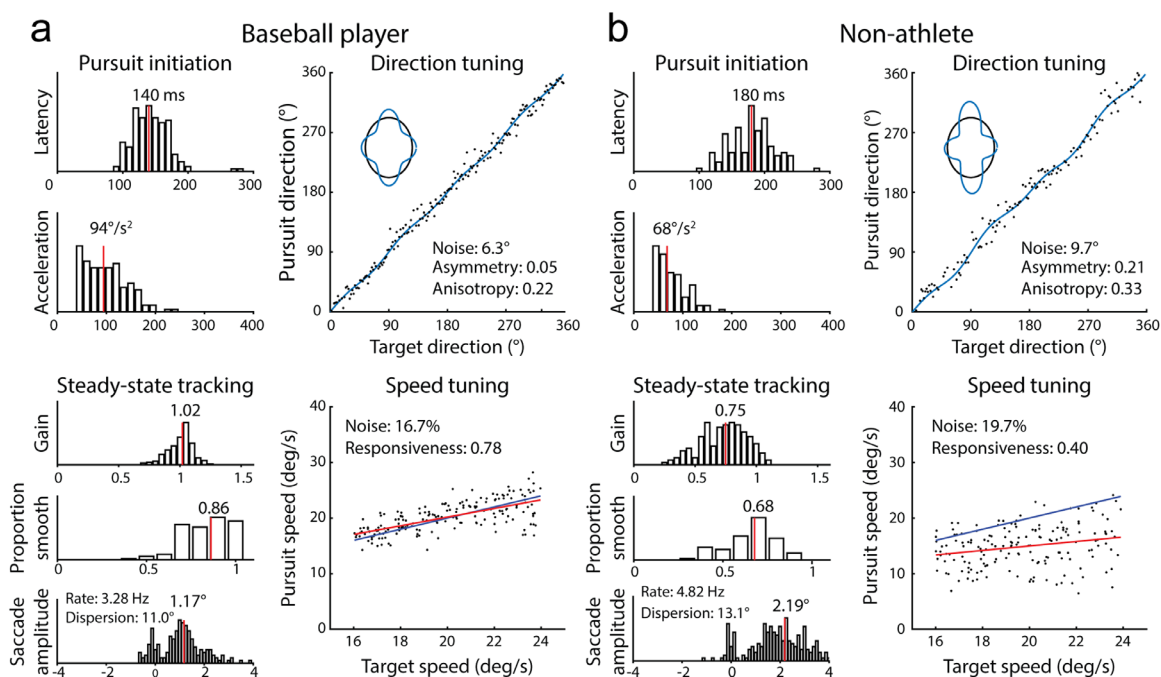


Figure 2. Summary of the 12 oculometric measures for (a) a typical baseball player and (b) a nonathlete. Histograms in the left column of both (a) and (b) plot across-trial measurements of pursuit initiation and steady-state tracking; scatter plots in the right column show trial-by-trial measurements of direction-tuning and speed-tuning. The red vertical line in each histogram indicates the median. The direction-tuning plot shows pursuit direction as a function of target direction for each trial. The local linear-regression slope of the fitted blue curve indicates direction gain; the inset illustrates the polar plot of “cloverleaf” direction-gain asymmetry and anisotropy (blue line) referenced to the circle of unity gain (thin black line). The speed-tuning plot shows pursuit speed as a function of target speed for each trial. The blue line indicates perfect performance. The slope of the fitted red line indicates speed responsiveness. Qualitative comparison of panels (a) and (b) illustrates some of the functional differences in the raw data associated with being a baseball player.

To examine the discrimination power of our oculometric measures to separate baseball players from nonathletes, we computed the area under the Receiver Operating Curve (i.e., ROC area) of the two distributions for our two populations of participants, which quantifies the ability of an ideal observer to discriminate one sample at random from one of the two distributions (Green & Swets, 1966). Values of 0.70 and higher are usually considered strong effects (Hosmer, Lemeshow, & Sturdivant, 2013). For our oculometric measures, the ROC area for steady-state gain (0.77) and direction noise (0.72) exceeded this criterion, indicating these two measures have strong discrimination power to separate baseball players from nonathletes.

Note that, consistent with previous sports vision literature (Laby et al., 1996; Schneiders et al., 2010; Winograd, 1942), an independent-samples  $t$  test showed that our baseball players had better binocular Freiburg visual acuity (Bach, 1996) than the nonathletes ( $t(84) = 3.47$ ,  $p < 0.001$ , Cohen’s  $d = 0.75$ ). However, across both the baseball player and the nonathlete participants in the current study, visual acuity was not significantly correlated with any of the 12 oculometric measures

(Pearson’s  $r(86) \leq 0.25$ ,  $p \geq 0.22$  after Holm’s sequential Bonferroni correction for multiple correlations; see also Liston & Stone, 2014). This indicates that visual acuity is not a contributing factor to the better ocular-tracking performance observed in baseball players. Furthermore, it has been reported that there is no significant difference in the static visual acuity among professional Japanese baseball players at different performance levels (Hoshina et al., 2013), indicating that visual acuity is also not a predictor of baseball performance level.

To further examine the overall ocular-tracking performance difference between the baseball players and nonathletes, we combined the 12 oculometric measures to compute the ocular-tracking performance index for each participant (see Methods). The index value indicates how closely an individual participant’s ocular-tracking performance matches the average performance of the baseball players. Figure 4a plots the histograms of the ocular-tracking performance index and the fitted Gaussian curves for the two participant groups. An independent-samples  $t$  test showed that the values of the ocular-tracking performance index were significantly higher for the baseball players than

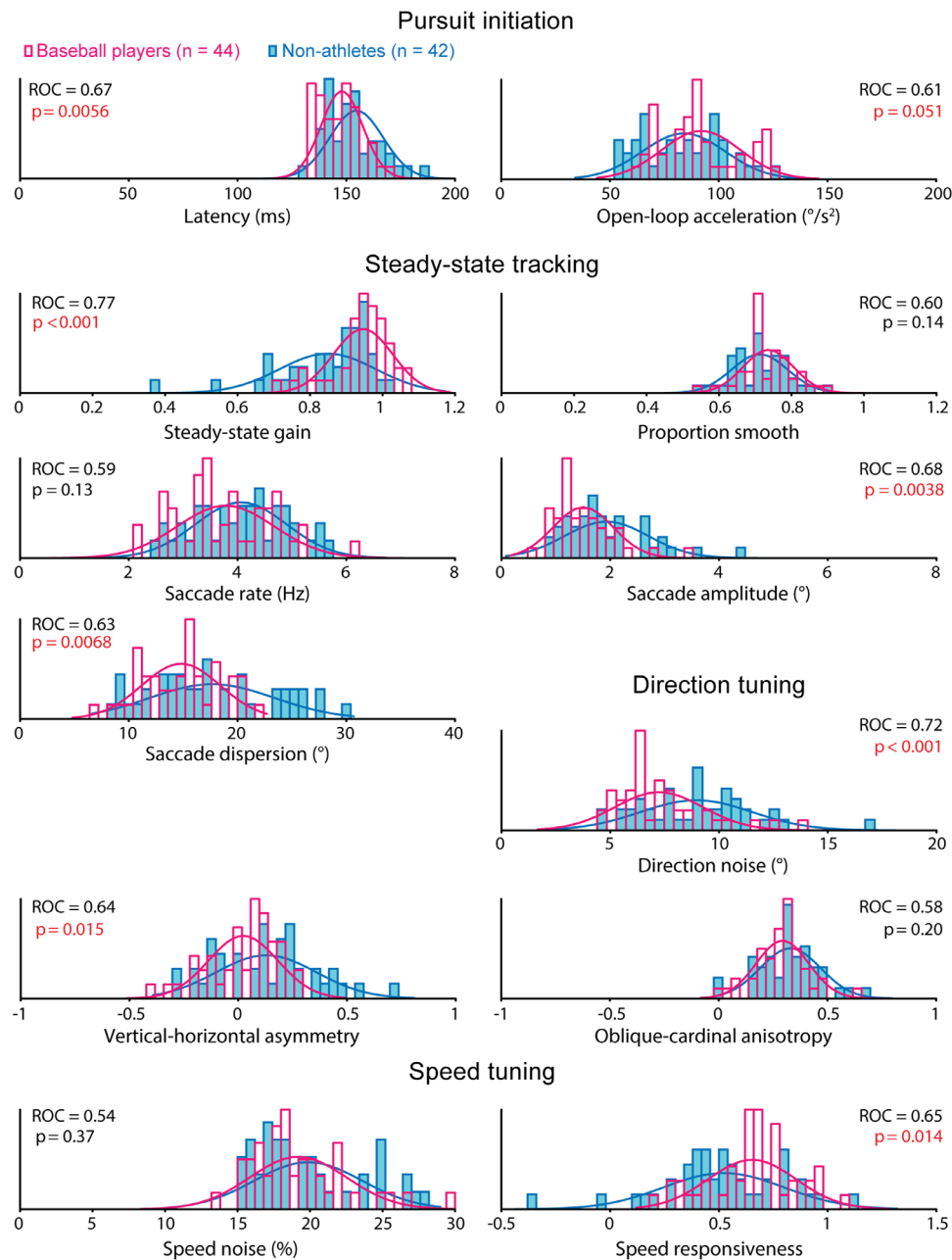


Figure 3. Histograms and Gaussian fits of the 12 oculometric measures for 44 baseball players (magenta bars and lines) and 42 nonathletes (blue bars and lines). ROC values indicate the area under the ROC curve of the two distributions, which quantifies the ability of an ideal observer to discriminate one sample at random from one of the two distributions.

for the nonathletes ( $t(84) = 4.66$ ,  $p < 0.001$ , Cohen's  $d = 1.00$ ), indicating that the baseball players had overall better ocular-tracking capabilities than did the nonathletes. In addition, the ROC area for the ocular-tracking performance index (0.79) was larger than that for each of the 12 oculometric measures (see Figure 3) and exceeded 0.70, indicating that the combined ocular-tracking performance index has strong discrimination power to separate baseball players from nonathletes.

To examine whether the baseball player's position (infielder, outfielder, pitcher, or catcher) in the field affected ocular-tracking performance, we conducted a one-way analysis of variance (ANOVA) with player position as a categorical variable on each of the 12 oculometric measures. We did not find a significant effect of player position on any of the 12 oculometric measures ( $F(3, 43) < 2.55$ ,  $p > 0.069$ ,  $\eta^2 < 0.16$ ). A one-way ANOVA with player position as a categorical variable on the ocular-tracking performance index also



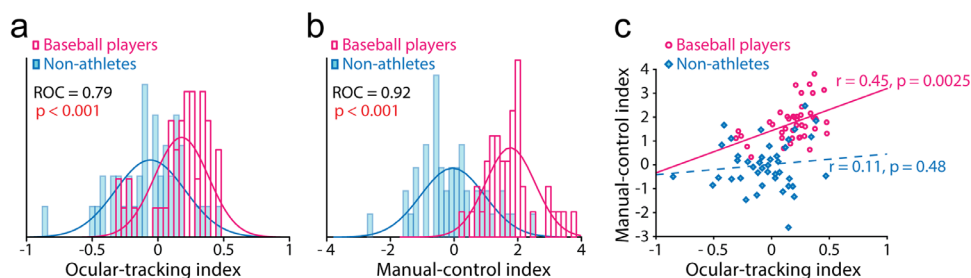


Figure 4. Histograms and Gaussian fits of the (a) ocular-tracking and (b) manual-control performance indices for 44 baseball players (magenta bars and lines) and 42 nonathletes (blue bars and lines). (c) Manual-control performance index against ocular-tracking performance index for 44 baseball players (magenta circles) and 42 nonathletes (blue diamonds). The baseball players showed a significant correlation between ocular-tracking and manual-control performance index that is absent in the nonathletes.

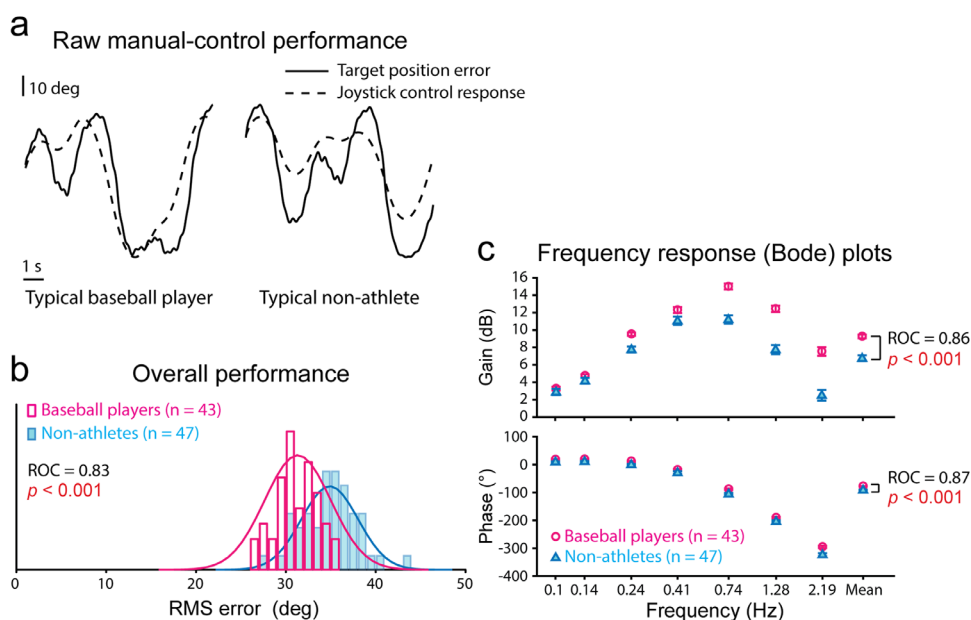


Figure 5. (a) Representative 13 s of raw manual-control performance for a typical baseball player (left panel) and a typical nonathlete (right panel). The solid line depicts the input target position error and the dashed line depicts the output joystick control response. (b) Histograms and Gaussian fits of the RMS error of the target position for 43 baseball players (magenta bars and lines) and 47 nonathletes (blue bars and lines). (c) Frequency-response (Bode) plots of the manual-control performance for 43 baseball players (magenta circles) and 47 nonathletes (blue triangles). The upper panel illustrates the mean response amplitude (gain) and the lower panel illustrates the mean response delay (phase lag) averaged across participants. The rightmost data points illustrate the mean averaged across input perturbation frequencies. Error bars are  $\pm 1 SE$  across participants.

did not reveal any significant effect of player position ( $F(3, 43) = 1.21, p = 0.32, \eta^2 = 0.083$ ). These results indicate that the baseball player’s position does not have a significant relationship with ocular-tracking performance.

**Manual-control performance**

Figure 5a plots the input target position error and the output joystick control during a sample 13 s in the first half of a 95-s trial for a typical baseball player and

a typical nonathlete. They both showed scaled control response to the input target position error with the response at the highest frequencies smoothed out. The baseball player showed larger responses with greater phase lead than did the nonathlete, echoing the reported previous findings that athletes in general are exceptional in their anticipatory sensorimotor skills compared with general population (Muller & Abernethy, 2012).

Figure 5b plots the histogram of the RMS error of the target position for the 43 baseball players and the 47 nonathlete controls who completed the manual-control

task. An independent-samples  $t$  test revealed that the RMS error in degrees of visual angle (deg) was significantly smaller for the baseball players than for the nonathletes (mean  $\pm$  SD:  $31.15 \pm 2.30$  deg vs.  $34.88 \pm 3.16$  deg,  $t(88) = 6.36$ ,  $p < 0.001$ , Cohen's  $d = 1.34$ ), indicating that the baseball players' overall control performance was better than the nonathletes.

Figure 5c plots the manual-control response amplitude (i.e., gain) and response delay (i.e., phase lag) at each input perturbation frequency (i.e., the standard Bode plot) for both the baseball players and the nonathletes. A 2 (participant group)  $\times$  7 (frequency) mixed-design ANOVA on gain revealed that both the main effects of participant group and frequency were significant ( $F(1, 88) = 39.80$ ,  $p < 0.001$ ,  $\eta^2 = 0.31$  and  $F(6, 528) = 301.32$ ,  $p < 0.001$ ,  $\eta^2 = 0.77$ , respectively), and so was their interaction effect ( $F(6, 528) = 19.29$ ,  $p < 0.001$ ,  $\eta^2 = 0.18$ ). Gain increased with perturbation frequency at lower frequencies and then decreased with perturbation frequency at higher frequencies, which is a typical response characteristic for acceleration control dynamics (Li et al., 2005, 2016). Newman-Keuls post hoc tests revealed that while the baseball players did not differ from the nonathletes in gain at the four lower frequencies, they showed larger gain in the three highest frequencies (0.74–2.19 Hz:  $p < 0.001$ ), indicating that the baseball players were more responsive to high-frequency motion signals. An independent-samples  $t$  test showed that the mean gain averaged across seven input perturbation frequencies was also significantly larger for the baseball players than for the nonathletes ( $9.3 \pm 1.3$  dB vs.  $6.8 \pm 2.3$  dB,  $t(88) = 6.31$ ,  $p < 0.001$ , Cohen's  $d = 1.33$ ).

A 2 (participant group)  $\times$  7 (frequency) mixed-design ANOVA on phase lag revealed that both the main effects of participant group and frequency were also significant ( $F(1, 88) = 58.71$ ,  $p < 0.001$ ,  $\eta^2 = 0.40$  and  $F(6, 528) = 4764.15$ ,  $p < 0.001$ ,  $\eta^2 = 0.98$ , respectively), but their interaction effect was not significant ( $F(6, 528) = 1.30$ ,  $p = 0.25$ ,  $\eta^2 = 0.010$ ). As expected, phase lag increased with perturbation frequency. An independent-samples  $t$  test showed that the mean phase lag averaged across seven input perturbation frequencies was also significantly smaller for the baseball players than for the nonathletes ( $77.7 \pm 7.7^\circ$  vs.  $91.0 \pm 8.7^\circ$ ,  $t(88) = 7.66$ ,  $p < 0.001$ , Cohen's  $d = 1.62$ ), indicating that the baseball players initiated manual-control responses sooner than did the nonathletes across all frequencies.

For our manual control measures, the ROC area well exceeded 0.70 for all three measures (RMS error: 0.83; gain: 0.86; phase lag: 0.87), indicating that all of them have excellent discrimination power to separate baseball players from nonathletes.

To further examine the overall manual-control performance difference between the baseball players and the nonathletes, we combined all three manual-control

measures to compute the manual-control performance index for participant (see Methods). The index value indicates how closely an individual participant's manual-control performance matches the average performance of the baseball players. Figure 4b plots the histograms of the manual-control performance index and the fitted Gaussian curves for the two participant groups. An independent-samples  $t$  test showed that the values of the manual-control performance index were significantly higher for the baseball players than for the nonathletes ( $t(88) = 9.51$ ,  $p < 0.001$ , Cohen's  $d = 2.01$ ), showing that baseball players showed overall better manual-control capabilities than did the nonathletes. In addition, the ROC area for the manual-control performance index (0.92) was larger than that for each of the three manual-control measures (see Figure 5), indicating that the combined manual-control performance index also has excellent discrimination power to separate baseball players from nonathletes.

To examine whether the baseball player's position (infielder, outfielder, pitcher, or catcher) in the field had any effect on manual-control performance, we conducted a one-way ANOVA with player position as a categorical variable on each of the three manual-control measures. We did not find any significant effect of player position on any of the three measures ( $F(3, 42) < 1.45$ ,  $p > 0.24$ ,  $\eta^2 < 0.10$ ). A one-way ANOVA with player position as a categorical variable on the manual-control performance index also did not reveal a significant effect of player position ( $F(3, 42) = 0.54$ ,  $p = 0.66$ ,  $\eta^2 = 0.040$ ). These results indicate that the baseball player's position does not have a significant relationship with manual-control performance.

### Correlation between ocular-tracking and manual-control performance

To examine whether ocular tracking can predict manual-control performance, we examined whether there was any linear correlation between the 12 oculometric and the three manual-control measures. For the baseball players, two oculometric measures, steady-state gain and speed responsiveness, were significantly correlated with the RMS error in the manual-control task (Pearson's  $r(43) = -0.45$  and  $-0.47$ ,  $p = 0.030$  and  $p = 0.019$ , respectively, after Bonferroni correction), and no other significant correlations were found. For the nonathletes, no significant correlation was found between any oculometric and manual-control measures. This shows that for the baseball players, higher gain or speed responsiveness in ocular tracking can stochastically predict better performance in manual control, but no such prediction exists for the nonathletes.

To further examine the relationship between ocular-tracking and manual-control capabilities,

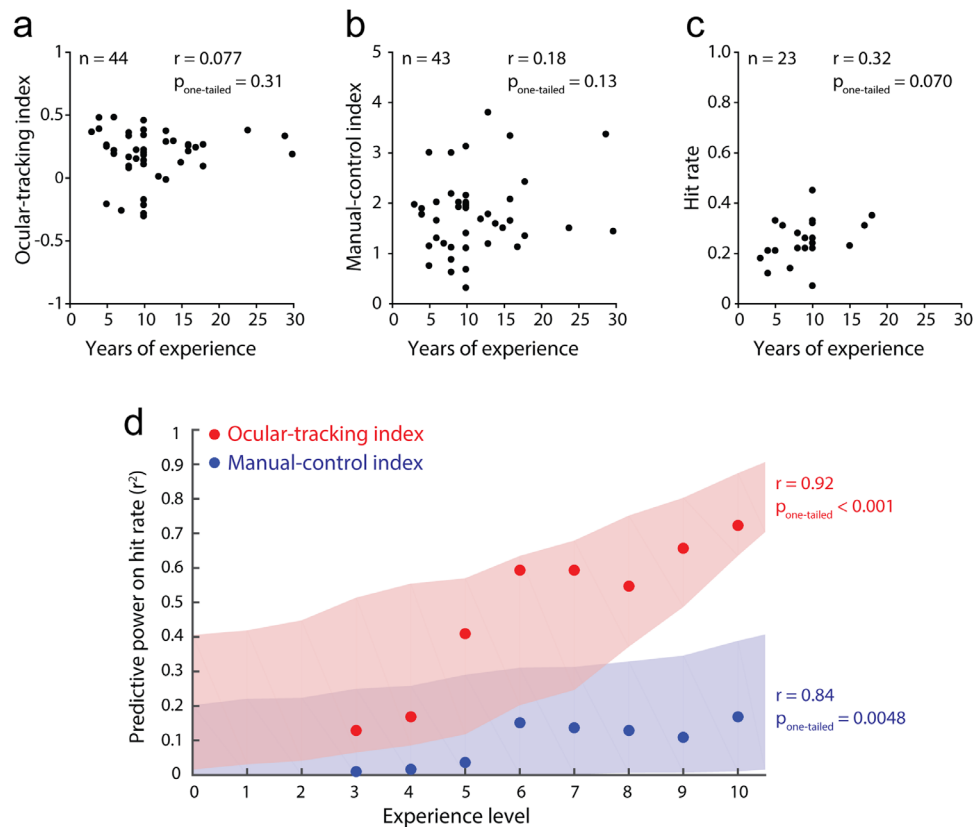


Figure 6. (a) Ocular-tracking performance index, (b) manual-control performance index, and (c) hit rate as a function of years of experience and (d) predictive power of performance indices (red dots: ocular tracking; blue dots: manual control) as a function of experience level. The colored areas indicate the 95% confidence intervals across simulations of the best-fitting linear additive-noise cascade model proposed in the Discussion (see Figure 7), with  $\xi_o$  (the noise scalar for the oculomotor system) = 0.23,  $\xi_m = 2.06$  (the noise scalar for the manual motor system),  $\xi_i$  (the intercept of the noise scalar for batting) = 2.15, and  $\xi_s$  (the slope of the noise scalar for batting) = 0.17, with the reduced  $\chi^2$  (9.59, 12) = 0.80.

we performed linear correlation analysis on the ocular-tracking and manual-control performance indices for each participant group (Figure 4c). We found that the two indices were significantly correlated for the baseball players (Pearson's  $r(43) = 0.45$ ,  $p = 0.0025$ ) but not for the nonathletes (Pearson's  $r(42) = 0.11$ ,  $p = 0.48$ ). This shows that ocular-tracking and manual-control capabilities are highly linked in the baseball players but not in the nonathletes. That is, while better ocular-tracking performance is associated with better manual-control performance for the baseball players, better ocular-tracking performance does not imply better manual-control performance for the nonathletes.

### Visuomotor predictors of batting performance

To find the visuomotor predictors of batting performance (hit rate), we first examined how ocular tracking, manual control, and batting performance change with years of experience in playing baseball. Figure 6 plots ocular-tracking performance

index (left panel), manual-control performance index (middle panel), and hit rate of batting performance (right panel) as a function of years of experience. Neither ocular-tracking (Figure 6a) nor manual-control performance (Figure 6b) showed any significant improvement with years of experience (Pearson's  $r(44) = 0.077$ ,  $p_{\text{one-tailed}} = 0.31$  and Pearson's  $r(43) = 0.18$ ,  $p_{\text{one-tailed}} = 0.13$ , respectively). One-tailed testing is justified because of the a priori assumption that the correlation would be positive. As expected, these two basic visuomotor skills were not changed by playing baseball. On the other hand, hit rate of batting performance (Figure 6c) showed a trend of improvement with years of experience (Pearson's  $r(23) = 0.32$ ,  $p_{\text{one-tailed}} = 0.070$ ), perhaps failing to reach full significance because of a smaller sample size—we only had access to the batting performance of the female players, with only three of them having more than a decade of experience, thus limiting the x-axis range. Note that although years of experience may correlate with age, there was no correlation between hit rate and age for these female baseball players (Pearson's  $r(23) =$

Years of experience	Ocular-tracking index			Manual-control index		
	<i>r</i>	<i>p</i> <sub>one-tailed</sub>	<i>n</i>	<i>r</i>	<i>p</i> <sub>one-tailed</sub>	<i>n</i>
≥3	0.36	0.044	23	0.098	0.33	22
≥4	0.41	0.029	22	0.13	0.29	21
≥5	0.64	0.0013	20	0.19	0.22	19
≥6	0.77	<0.001	18	0.39	0.061	17
≥7	0.77	<0.001	17	0.37	0.077	16
≥8	0.74	<0.001	16	0.36	0.094	15
≥9	0.81	<0.001	14	0.33	0.13	13
≥10	0.85	<0.001	12	0.41	0.11	11

Table 2. Pearson' *r* and *p* value for the correlation between ocular-tracking performance index and hit rate (left) and between manual-control performance index and hit rate (right) for each experience level.

–0.15,  $p = 0.49$ ). This was expected because increased age *per se* does not correlate with improved baseball hitting performance (e.g., Ng, 2017).

We then explored the predictive power ( $r^2$ ) of the ocular-tracking and manual-control performance indices on hit rate as a function of experience level (Figure 6d), with the cohort of baseball players with experience level  $N$  defined as those with  $N$  or more years of experience in playing baseball (Table 2). The predictive power for both indices on hit rate shows a significant linear increase with experience level (ocular tracking: Pearson's  $r(23) = 0.92$ ,  $p_{one-tailed} < 0.001$ ; manual control: Pearson's  $r(22) = 0.84$ ,  $p_{one-tailed} = 0.0048$ ). However, ocular-tracking performance indices showed systematically larger power than did manual-control performance indices in predicting hit rate. In fact, the correlation between hit rate and ocular-tracking performance index was significant at all experience levels, whereas that was never the case for manual-control performance index (Table 2).

## Discussion

It has been reported that compared with nonathletes, baseball players have greater dynamic visual acuity, presumably due to an improved ability to track moving targets with their eyes (Uchida et al., 2012). Our ocular-tracking results provide direct evidence for this view, showing that baseball players outperformed nonathletes in ocular tracking of an unpredictably moving target with, on average, 4% shorter pursuit latency, 11% larger steady-state pursuit gain, 19% smaller direction noise, 39% smaller vertical-horizontal direction asymmetry, 25% larger speed responsiveness, and 22% smaller saccadic amplitudes with 16% smaller direction dispersion. For our manual-control task, baseball players showed 11% smaller overall

performance error, 37% larger response amplitude, and 15% shorter response delay compared with nonathletes. The frequency (Bode) analysis further revealed that they were especially more sensitive to motion signals at the three highest frequencies tested (i.e., 0.74 Hz, 1.28 Hz, and 2.19 Hz) than nonathletes. It has been reported that apart from an improved level of physical strength, individuals with ball sports experience outperform nonathlete healthy controls in perception, anticipation, and decision-making functions (for a review, see Yarrow, Brown, & Krakauer, 2009). Our results extend these findings by showing that baseball players also have superior basic visuomotor skills compared with healthy nonathletes, manifested in both their ocular-tracking and manual-control performance.

The shorter pursuit latency and manual response delay observed for our sample of baseball players is consistent with the reported shorter visuomotor delay observed in tennis experts when performing a simulated ball interception task (Le Runigo, Benguigui, & Bardy, 2010). Note that pursuit latency, even in our sample of nonathletes (median: 152 ms), is still shorter than the average reaction time (around 200 ms) of highly skilled professional cricketers batting balls with unpredictable movement (McLeod, 1987). This confirms that eyes are faster than hands when responding to unpredictable target motion.

It has been reported that with the increase of hand-eye coordination training, visual gaze progressively assists the hand control in a predictive manner (Sailer, Flanagan, & Johansson, 2005). Our examination of the correlation between ocular-tracking and manual-control performance showed that for the baseball players, better overall ocular-tracking performance was correlated with better overall manual-control performance, but this correlation was absent in the nonathletes. This difference in correlation explains previous seemingly contradictory findings. Specifically, Fookien et al. (2016) reported strong relationship in varsity baseball players between smooth pursuit accuracy and manual response errors when anticipating to intercept a moving dot on a computer screen, whereas Cesqui, Mezzetti, Lacquaniti, and d'Avella (2015) reported insignificant trial-by-trial correlation between pursuit quality and catching performance in healthy nonathletes. Our results, for the first time, show that both pursuit gain and speed responsiveness are significantly correlated with the overall performance error in manual control for baseball players but not for nonathletes. Together with baseball players' superior performance in both ocular tracking and manual control compared with nonathletes, this suggests that, in athletes, the correlation between ocular and manual performance, driven by shared visual motion processing, is revealed by their having lower levels of motor noise or other downstream



inefficiencies that dominate the performance of nonathletes.

Given that unlike shooting in basketball or putting in golf, the baseball's flight trajectory is highly uncertain and thus the perception and identification of the ball's trajectory likely requires effective visual tracking, several studies examined whether expert baseball players could use eye and head movements to track the ball better than novices. Hubbard and Seng (1954) first used 35-mm films of professional batters to determine at what intervals during the ball's flight gross eye and head movements occurred. They found that batters could not keep their eyes on the ball until the point of contact (i.e., no pursuit eye movements were observed within roughly 150–200 ms prior to contact). This is not surprising because when a 100-mph fastball passes the batsman, the visual angular velocity is around 500°/s while the fastest pursuit eye movements recorded in humans are only about 90°/s (Watts & Bahill, 1990). Hubbard and Seng (1954) did not examine eye tracking in nonathletes. Bahill and LaRitz (1984) compared eye movements made by Brian Harper, a major league player, with those of college novice hitters. They confirmed the observations of Hubbard and Seng but also found that Harper could track the ball longer than the novice hitters.

Surprisingly, despite the previous studies that found that baseball players show better pursuit of a flying baseball than do nonathletes, none examined whether this ocular-tracking performance could predict batting performance. Our study is the first to explore that possibility. Our results show that two basic visuomotor capabilities, ocular tracking and manual control, are unaffected by baseball experience. They nevertheless both become more correlated with batting accuracy with increasing baseball experience. In particular, ocular-tracking performance becomes a significant predictor of batting accuracy across players with  $\geq 3$  years of experience, accounting for more than 70% of the variance in batting performance across players with  $\geq 10$  years of experience. On the other hand, there is no significant correlation between manual-control performance and batting accuracy at any level of experience. This shows that ocular-tracking capability is highly sensitive in predicting baseball batting accuracy and can be used to gauge potential future batting capability of baseball players.

The correlation we found between batting accuracy and ocular tracking is surprising given the fact that our ocular-tracking task bears minimal similarity to pursuit tracking during baseball batting. The fact that we found such a correlation indicates that our ocular-tracking task measures fundamental dynamic visual and visuomotor capabilities that can generalize across tasks and our oculometric indices are good indicators of such basic capabilities. Indeed, our ocular-tracking task has been successfully used to examine perceptual expansion

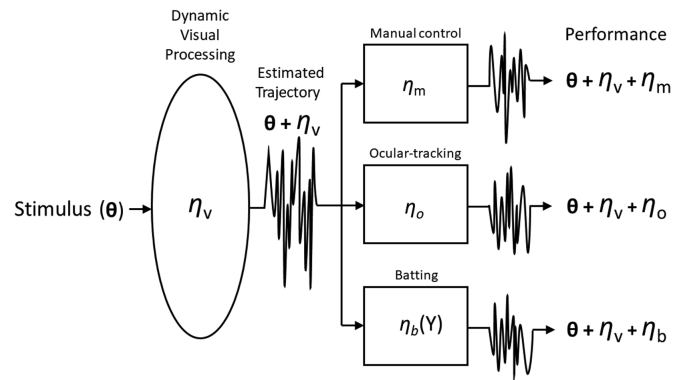


Figure 7. Illustration of the noise cascade model with additive noise in manual-control, ocular-tracking, and batting performance.

of direction space (Krukowski & Stone, 2005), as well as sensorimotor impairment associated with traumatic brain injury (Liston, Wong, & Stone, 2017), low-dose alcohol intake (Tyson et al., 2020), and acute sleep loss and circadian misalignment (Stone et al., 2019). It is, however, important to note that none of the baseball players in the current study were professional, and thus future research is needed to confirm the generalizability of our findings to elite professional baseball players and to skilled performance in other sports.

If the borderline correlation observed between hit rate and years of baseball experience is real (Figure 6c), which is very likely the case, albeit somewhat obscured in this study because of our skewed sampling (see Results), a simple linear additive-noise cascade model can explain and unify our many seemingly disparate findings. Figure 7 illustrates a model with additive independent noise sources in three visuomotor branches. The model's first assumption is that the three branches share a noisy visual front end that is the rate-limiting noise in ocular-tracking performance with the noise in visual motion processing denoted by  $\eta_v$ . This is supported by the findings that the noise in pursuit speed (Kowler & McKee, 1987) and direction (Stone & Krauzlis, 2003) provides indirect yet reliable measures of the noise in the visual perception of speed and direction, with little additional noise added by the oculomotor system. The small noise source in the oculomotor system ( $\eta_o$ ) is given by  $\eta_o = \xi_o \times \eta_v$ , with  $\xi_o$  the noise scalar for the oculomotor system.

The model's second assumption is that the motor system generates additional independent manual motor noise ( $\eta_m$ ) that adds to the overall noise observed in manual-control performance, which is given by  $\eta_m = \xi_m \times \eta_v$ , with  $\xi_m$  the noise scalar for the motor system. Lastly, the model's third assumption is that there is additional independent batting noise ( $\eta_b$ ) added to the batting performance that decreases monotonically with baseball experience and affects batting accuracy, which

is given by  $\eta_b = (\xi_i - \xi_s \times \text{experience level}) \times \eta_v$ , where  $\xi_i$  represents the intercept and  $\xi_s$  represents the slope of the linear trend in batting noise.

With the above assumptions, we determined the four model parameters ( $\xi_o$ ,  $\xi_m$ ,  $\xi_s$ ,  $\xi_i$ ) by a best fit to the 16 data points in Figure 6d using a least squares procedure with 1,000 Monte Carlo simulations of the different sources of noise. The reduced  $\chi^2$  of the model fit was 0.8, indicating that it can explain the high predictive power of ocular-tracking over manual-control performance on hit rate that increases with experience level (see Figure 6d). With the same fitted parameters, the model also independently quantitatively reproduces the observed significant correlation between ocular-tracking and manual-control performance indices in baseball players (mean and 95% confidence intervals of Pearson's  $r$ : 0.43 [0.17, 0.65]; see Figure 4c). Last, the model can also explain the observed insignificant correlation in nonathletes shown in Figure 4c simply by fitting a new value of  $\eta_m$  to the nonathlete data to capture the fact that nonathletes in general have higher manual motor system output noise ( $\eta_m = 8.37 \times \eta_v$ ) than do baseball players ( $\eta_m = 2.06 \times \eta_v$ ), with all other parameters remaining the same. The higher  $\eta_m$  in nonathletes then dominates over  $\eta_v$  to conceal any correlation. The lower  $\eta_m$  in baseball players is presumably due to selection and training. Note that although this simple linear additive-noise cascade model with no nonlinearities or interactions explains our data well, we do not rule out the possibility that a more complex model with added nonlinear features, interactions, or nonindependent or multiplicative noise sources might fit our data better (at the expense of added complexity). What our model simulations capture is the fact that the data of this study can be successfully accounted for when ocular tracking, manual control, and baseball batting depend on significant shared noise in upstream visual processing of motion signals.

In summary, the present study shows that compared with nonathletes, baseball players have better basic visuomotor skills in ocular tracking and manual control due to selection for innate capabilities but not due to experience in playing baseball. They both, however, become more correlated with batting accuracy with increasing baseball experience, with ocular-tracking capabilities highly predictive of batting accuracy. Our study thus provides the first evidence of a reliable visuomotor predictor of batting accuracy in baseball players, increasingly so with increasing experience level. The findings of the current study suggest that the complex, learned skill of batting is limited by fundamental dynamic visual and visuomotor capabilities and that this limitation becomes increasingly apparent with experience, as extraneous nonvisual sources of performance noise and inefficiencies are trained out. The findings are consistent

with a common front-end visual motion-processing element that is performance limiting in athletes for all three visuomotor tasks, independent of complex task-specific later processing, decision making, or motor output.

*Keywords:* eye movements, manual control, sports vision, baseball batting, visuomotor control

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