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Estimation bias and serial dependence in speed perception

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Abstract

Studies have found that feature estimates are systematically compressed towards the distribution center, showing a central tendency. Additionally, the estimate of current features is affected by the previously seen feature, showing serial dependence or adaptation effect. However, these all remain unclear in the speed estimation. To address this question, we asked participants to estimate the speed of moving Gabor patches. In Experiment 1, speeds were selected from three uniform distributions with different lower and upper boundaries (i.e., slow, moderate, and fast ranges). In Experiment 2, speeds were arranged in an increasing, uniform, or decreasing distribution. The boundaries of three distributions were the same. The results found that speed estimates were systematically compressed towards the center of the uniform distribution center, showing a central tendency, and its size increased with the range boundaries. However, in the decreasing and increasing distributions, aside from central tendency, the speed estimates were also showed a bias away from the heavy tail of the distributions. Moreover, there was an attractive serial dependence that was not affected by the speed range. In summary, the current study, along with previous studies that reveal a slow-speed bias, comprehensively reveals various estimation biases in speed perception.

Keywords Speed perception, Central tendency, Serial dependence, Slow-speed bias, Efficient encoding, Bayesian decoding

Introduction

It is crucial for animals to accurately estimate speed in order to survive. For instance, when an antelope detects a leopard accelerating its pace, it must also rapidly increase its own speed in order to seize the fleeting opportunity. Similarly, when driving on the road, it is necessary to capture the changes in the speed of the car in front to avoid a collision. Given the importance of this ability, numerous researchers have conducted extensive studies to reveal the estimation bias and the related factors. In general, studies have found that the speed is generally underestimated, showing a slow-speed bias [38, 40, 46]. Some researchers argue that this bias is due to the structure of the past experience learned in daily life or the evolutionary process, known as the prior. In the prior, the proportion of slow speeds is significantly higher than that of high speeds [38, 39]. Additionally, the speed estimation is consistent with a Bayesian decoding process, in which observers generate a posterior distribution about the current stimulus by optimally combining its representation (i.e., likelihood) with the prior. The final speed estimate is derived from the posterior distribution [38, 39].

In most of speed estimation studies, the speeds are generally simulated by moving a Gabor patch and selected from a broad range, e.g., [0.5, 12] deg/s in Stocker and Simoncelli, [39] and [1, 12] deg/s in Sotiropoulos et al. [38]. However, at a specific point in time in the real

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world, the speed is always constrained to a short range. For example, the speed for a healthy adult is within the range of 0.77 to 1.79 m/s when walking [28]; the speed is within the range of 80 to 120 km/h when driving on a highway in China. It is therefore unclear how participants estimate speed when speeds are limited to a certain range. This is the first question addressed in the current study.

Previous studies have found that a central tendency is presented in visual perception, meaning that when the stimulus feature is selected from a limited range, the feature estimate is symmetrically compressed toward the range center. For example, Jazayeri and Shadlen [22] asked participants to estimate a time-interval estimation task. Each participants completed three sessions of trials. On each trial of each session, the time interval was randomly selected from a range of time-intervals that was varied among sessions. They found that the estimates of time-intervals were systematically compressed towards the range center, showing a central tendency (see also Ryan [36], . Similar tendency has been revealed in various visual features, including line length estimation [3, 13, 21], facial expressions [12, 35], and color [30, 31]. In the present study, we sought to examine whether speed estimation was centrally dependent.

Additionally, extensive studies have found that the estimate of the currently presented feature is affected by the previously presented feature. This effect can be either attractive or repulsive [2, 5, 9]; Cicchini et al. Fritsche et al., [16] 2023; Moon & Kwon [27, 32, 37, 45], . It has been proposed that the attractive serial dependence can assist observers in maintaining the world continuity [14], while the repulsive serial dependence can improve our perceptual sensitivity [2, 45]. Both types of serial dependences have been observed in various features, but they remain unclear in speed perception. It is well established that being alert to changes in speed can help us to avoid danger in time. However, sometimes or in most cases, we need to propose that the speed maintains constant in a short-time window, so that we can save limited cognitive resources. When a danger event occurs, we can allocate these resources to the event and capture it timely. Accordingly, the aim of this study was to examine the effects of the previous speed on the current speed estimation.

Moreover, for the computational mechanisms, previous studies have found that both central tendency and serial dependence are consistent with the Bayesian inference process. That is, when the uncertainty of the physical feature is decreased, the estimate will be biased more towards the previous experience Knill & Richards, [23]. The previous experience can be either the distribution of the features with certain range (e.g., Ashourian & Loewenstein [3], Jazayeri & Shadlen, [22]; Olkkonen & Allred [30, 31], or the internal representation (i.e., likelihood) of the previously seen feature (e.g., Gallagher & Benton [10, 18], see Cicchini et al., [11]for a review). Previous studies have found that the certainty (i.e., discrimination sensitivity) of speeds decreases with the increase of speed [39]. Therefore, it can be expected that the central tendency increases with the increase of speed (or speed range), and when the currently presented speed was high, the serial dependence could be also stronger.

In summary, the current study examined whether the speed estimation showed central tendency and serial dependence. To address these questions, two experiments were conducted. In Experiment 1, the speeds were selected from three uniform distributions with different boundaries. In Experiment 2, the speeds were selected from a decreasing, uniform, or increasing distribution.

Experiment 1 Uniform distributions with different boundaries

Experiment 1 was designed to examine the presence of central tendency and serial dependence in speed estimation, utilizing three uniform distributions with varying lower and upper boundaries.

Methods

Participants

Thirty participants (20 females, 10 males, 18–25 years old) were recruited from Zhejiang Normal University. All were naïve to the experimental purpose and had normal or corrected-to-normal vision. The experiment was approved by the Scientific and Ethical Review Committee in the Department of Psychology of Zhejiang Normal University, which is in accordance with the Declaration of Helsinki.

Stimuli and apparatus

In each trial of the current experiment, a vertical Gabor patch (4.39 H ×4.64 V degrees; 200 H × 200 V pixels; Fig. 1 a) was presented against a gray background (8.73 cd/m^2; RGB: [110 110 110]). The spatial frequency of the Gabor patch was 1 cycle/deg (CPD). The luminance of the darkest and lightest areas of the stimuli were 27.87 cd/m^2 and 0.73 cd/m^2. Each stimulus horizontally shifted to the right. The motion speed was randomly selected from three ranges: [0.88 deg/s, 6.15 deg/s], [3.51 deg/s, 8.78 deg/s], and [6.15 deg/s 11.42 deg/s], labeled as low-speed, moderate-speed, and high-speed distributions. The speed in each range was increased with a step of 0.66 deg/s.

Additionally, a static mask stimulus (Fig. 1 d) was generated that included 100 (10×10) gray squares. The

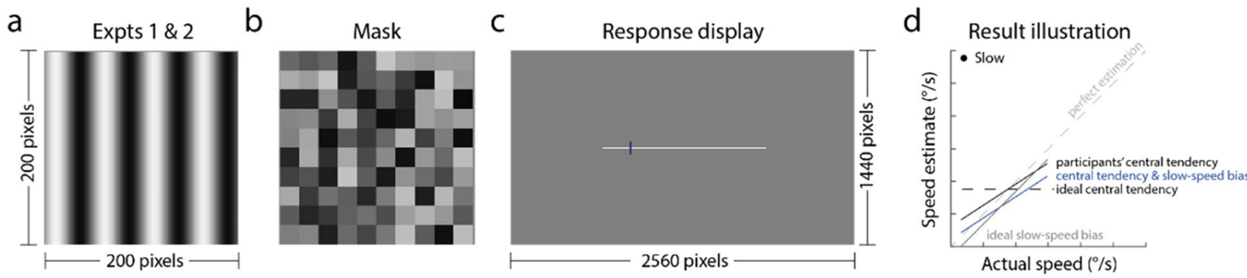

Fig. 1 Stimulus illustrations used in the current study. **a** An example of a vertical Gabor patch used in Experiments 1 and 2. **b** Mask illustration that consists of 100 Gy squares, the illuminances of the squares are randomly selected from the range of [27.87 cd/m^2, 0.73 cd/m^2]. **c** Response display in which a horizontal line (1300 pixels) is in the mid-section of the display, and a vertical mouse-controlled blue probe is on the line. **d** Illustrations of different linear fitting results in the slow-speed distribution

luminance of each square was randomly selected from the range of [27.87 cd/m^2, 0.73 cd/m^2].

The displays were programmed in MATLAB using the Psychophysics Toolbox 3 and presented on a 27-inch Dell monitor (resolution: 2560 H× 1440 V pixels; refresh rate: 60 Hz) with NVIDIA GeForce GTX 1660Ti graphics card.

Procedure

All participants sat in a lighted and quiet room with their heads stabilized with a chin-rest at a viewing distance of 56 cm. Before the start of the experiment, participants' straight-ahead direction was aligned with the display center. On each trial, the Gabor stimulus was presented for 200 ms, followed by a 200-ms mask display (Fig. 1b). Note that a 200-ms Gabor and 200-ms mask can inhibit the generation of motion aftereffect, which had been confirmed with participants' report in the pilot study. After the mask display, a gray horizontal line (length: 28.34 degrees) appeared in the mid-section of the display, and a mouse-controlled probe was on the gray line (Fig. 1c). Participants were asked to move the probe to indicate their speed estimate. The left endpoint indicated that the Gabor was static (i.e., speed was 0 deg/s); the right endpoint indicated that the Gabor moved at a speed of 12.21 deg/s. When the participants clicked the mouse button, the next trial started immediately.

The current experiment consisted of three blocks. Each block corresponded to one speed range: [0.88 deg/s, 6.15 deg/s], [3.51 deg/s, 8.78 deg/s], or [6.15 deg/s, 11.42 deg/s]. Each block first started with 40 practice trials, the speeds of which were randomly selected from 3.07 deg/s, 6.15 deg/s, 9.22 deg/s, or 12.29 deg/s. Each repeated 10 times. This manipulation aimed to help participants familiarize the speed distribution on the response line (Fig. 1e). After the 40 trials, 180 trials were followed, the speeds of which were randomly from the nine speeds in the corresponding speed range. Each speed was repeated 20 times.

Before starting the experiment, the experimenter first introduced the experimental task and showed Gabor stimuli with 0 deg/s, 3.07 deg/s, 6.15 deg/s, 9.22 deg/s, and 12.29 deg/s. Meanwhile, the experimenter told participants to move the probe to the left endpoint, quartile point, middle point, three-quarter point, and right endpoint along the response line, respectively. After the instruction, participants were given 20 practice trials, the speeds of which were randomly 0 deg/s, 3.07 deg/s, 6.15 deg/s, 9.22 deg/s, or 12.29 deg/s. After the practice, the experiment started. The conducting sequences of the three blocks were counterbalanced among participants. The experiment lasted for about 20 min.

Data analysis

Estimation bias

The speed estimate (*SE*) was recorded. To examine whether the speed was central tendent or low-speed biased, we first fitted the speed estimate as a linear function of the actual speed (*AS*), given as:

$$SE = \mathrm{c} \times AS + \mathrm{r}$$

where c represents the slope. If central tendency is in the speed estimation, the c will be negative; in contrast, if c is positive, then central repulsion is in the speed estimation. r represents the intercept, meaning the speed estimate residual when the actual speed was 0 deg/s. Note that when the *SE* equals to the *AS* (dashed diagonal line in Figs. 1 d and 2 a), c will be 1, indicating that participants perfectly estimate the speed; when the *SE* is systematically compressed towards the range center (solid colored lines in Figs. 1 d and 2 a), showing central tendency, c will be smaller than 1, and the stronger the central tendency is, the smaller the c is.

Additionally, to estimate whether there was a slow-speed bias, we calculated the speed estimate (SE_{Center})

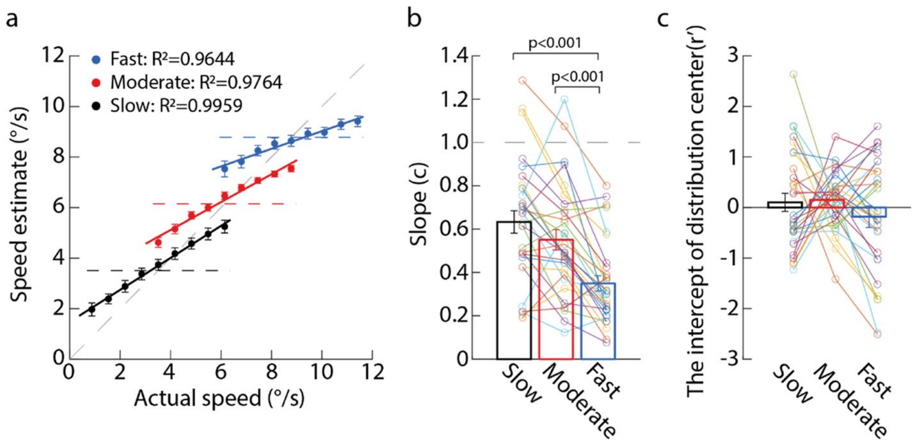

Fig. 2 Results of estimation bias in Experiment 2. **a** The speed estimate is against the actual speed. The black, red and blue dots correspond to the increasing, uniform, and decreasing distributions. Each dot indicates the mean speed estimate averaged across 30 participants. Error bars are the standard error across 30 participants. Solid lines are the best fitting results of Eq. 1. **b** and (**c**) plot the slope (**c**) and the intercept of distribution center (r', the difference between the speed estimate when the actual speed was the distribution center and the range center) against three distributions (increasing, uniform, and decreasing). Error bar is the standard error across 30 participants. Circles correspond to the participants' data

when the *AS* was the range center and used the SE_{Center} to minus the range center. This difference, represented by r′, could indicate whether slow-speed bias was in the speed estimation. Specifically, if the sign of r′ was negative, the speed estimate was biased towards the slow-speed side; in contrast, if the sign of r′ positive, the speed estimate was biased towards the high-speed side (Fig. 1 d).

Here, we used the low-speed distribution to illustrate the potential results. As shown in Fig. 1 d, the dashed gray oblique line indicates that observers accurately estimate the speed, showing a perfect estimation where c=1 and r'=0. The dashed dark horizontal line indicates that the speed estimate is always the center of the speed range, showing an ideal central tendency where c=0 and r'=0. The solid gray line indicates that the speed estimate was accurate but systematically biased towards the slow speed, showing an ideal slow-speed bias where c=1 and r'<0. The solid blue line indicates that the speed estimate was systematically biased towards the slow speed and the center of the speed distribution, showing that the speed estimation was both central tendency and slow-speed biased where c<1 and r'<0.

Serial dependence

To examine serial dependence, we first calculated the estimation error of each trial which was the difference between the speed estimate and the actual speed. Then, we calculated the difference in the actual speed between the previous 1st trial and the current trial, named as the relative speed of pre-trials (RS_{pre}). The negative relative speed of pre-trials (RS_{pre_neg}) means that the speed of previous trials was slower than that of the current trial, and vice versa (RS_{pre_pos}). If the relative speed of pre-trials is zero (RS_{pre_0}), then the speeds of the previous trial and the current trial were the same. Next, we calculated the mean estimation errors of current trials as the relative speed of pre-trials was negative, zero, and positive. Finally, we took the mean estimation error of RS_{pre_0} as the baseline and used the mean estimation error of RS_{pre_neg} (RS_{pre_pos}) to minus the above estimation error. The differences were named as the relative mean estimation errors (REE_{pre_neg}, REE_{pre_pos}).

Several previous studies have revealed that the central tendency was correlated with serial dependence. In particular, some studies argued that serial dependence and central tendency effects are two facets of the same phenomenon (Boboeva, Pezzotta, Clopath, & Akrami [7], ; Wang, Luo, Ivry, Tsay, & Pöppel, [48]); and some studies also found that the two effects could be mutually predicted by each other [19]; Sun, Zhang, Wang, Gong, & Dong, [41]. To get the pure serial dependence (i.e., removing the effect of central tendency on serial dependence), an additional analysis was employed. Specifically, as we all know, an unpresented feature cannot affect the perception of the presented feature. That is, the speed presented after the current trial cannot affect the estimation of the speed in the current trial. Accordingly, we repeated the above procedures except that the relative speed was the difference in the actual speed between the trial after the current trial (i.e., the unpresented 1st trial). To differentiate the REE_{pre} induced by previously presented trials, here we named the REE_{next} (REE_{next_neg} and REE_{next_pos}) meaning the REE induced by next, unpresented trials. If the correlation between the REE_{next} and the relative speed (RS) was significant, then the REE_{nex} indicates the error induced by other non-serial dependence factors.

Next, to remove the effects of non-serial dependence factors, we used the REE_{pre_neg} to minus the REE_{next_neg} and the REE_{pre_pos} to minus the REE_{next_pos}. These differences were named as the corrected relative estimation error (CREE). If the speed estimation was serial dependent, then CREE was negative (positive) when the RS was negative (positive).

Results

Estimation bias

To examine the estimation bias, we fitted the speed estimate as a linear function of the actual speed (Eq. 1) in the three ranges, as shown in Fig. 2 a. Black, red and blue dots show participants' performance in slow, medium, and fast speed ranges. The linear functions explained more than 96.44% variances. In Fig. 2 a, the gray diagonal line indicates that the speed estimates are the same as the actual speeds, showing the perfect estimation (Fig. 1 d). The horizontal dashed lines indicate that the speed estimate is always the center of each range, showing an ideal central tendency (Fig. 1 d). Figure 2 a shows that the speed estimates are between the ideal central tendency and the perfect estimation, suggesting that the speed estimate is central tendent.

Figure 2 b plots the slope (c) of the linear function against the three ranges. One sample *t* test showed that the slopes were all significantly smaller than 1 (Slow: Mean ± SD, 0.63 ± 0.28, $t(29)$ =-7.12, $p < 0.001$, Cohen's d = 2.64; Medium: 0.55 ± 0.26, $t(29)$ =-9.57, $p < 0.001$, Cohen's d = 3.56; Fast: 0.35 ± 0.20, $t(29)$ = -18.11, $p < 0.001$, Cohen's d = 6.73). These suggested that central tendency was present in the speed estimation. Additionally, Fig. 2 b also shows that the slope decreases with the increase of the speed range, which was supported by one-factor repeated measures ANOVA ($F(2,58) = 27.67$, $p < 0.001$, $\eta^2 = 0.49$). Further simple-effect analysis with Bonferroni correction showed that the slope of the slow range was significantly larger than that of the fast range ($p < 0.001$), and the slope of the moderate range was between the slow and fast range. These suggested that the size of the central tendency increased with the boundary of the speed range.

Figure 2 c plots the intercept of the range center (r') against the three ranges. It clearly shows that all r' are around 0. One sample *t* test showed that none of the intercepts (rs) in the three ranges was significantly different from 0 (Slow: Mean ± SD, 0.10 ± 0.98, $t(29) = 0.57$, $p = 0.58$, Cohen's d = 0.038; Medium: 0.15 ± 0.57, $t(29) = 1.44$, $p = 0.16$, Cohen's d = 0.055; Fast: -0.18 ± 1.16, $t(29)$ = -0.86, $p = 0.40$, Cohen's d = 0.32). These suggested that the speed estimation was not low-speed biased in the current study. Additionally, these results indicate that the r's were not significantly different among different ranges, which was supported by one-factor repeated measures ANOVA (Greenhous-Geisser corrected: $F(1.22,35.31) = 0.92$, $p = 0.36$, $\eta^2 = 0.031$).

Serial dependence

Figure 3 plots the results of serial dependence. It clearly shows that the corrected relative estimation error (CREE) when the speed of the previous 1st trial was slower than

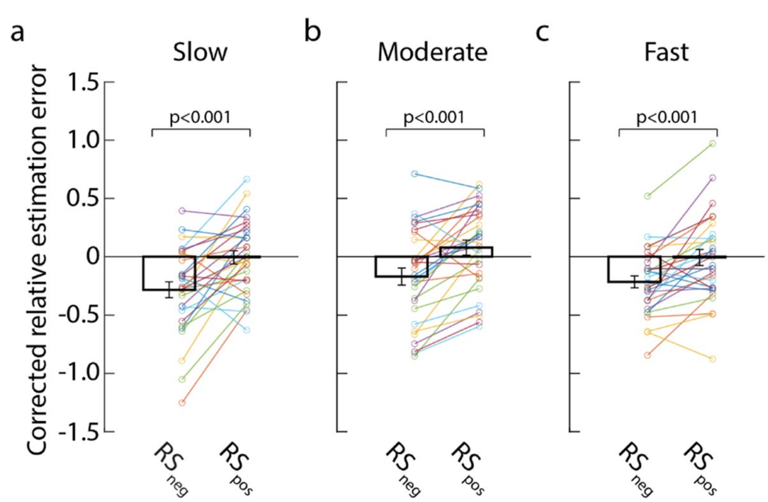

Fig. 3 Serial dependence results of Experiment 1. **a**–**c** correspond to the slow, moderate, and fast ranges. In each panel, the left and right bars correspond to the negative and positive relative speed (RS). The relative speed means the difference in the actual speed between the previous 1st trial and the current trial. RS_{neg} and RS_{pos} mean that the speed of the previous 1st trial is slower and faster than the speed of the current trial. Error bar is the corrected relative estimation error (CREE) across 30 participants. Circles correspond to the participants' data

that of the current trial (RS_{neg}) was more negative than that when the speed of the previous 1st trial was faster than that of the current trial (RS_{pos}). A repeated measures ANOVA with the relative speed (RS_{neg} vs. RS_{pos}) and speed ranges (slow, moderate, fast) as the within-subject factors showed that only the relative speed was significant ($F(1,29)=40.64$, $p<0.001$, $\eta^2=0.58$), and the CREE in the RS_{neg} (Mean ± SE: -0.23 ± 0.043) was more negative than that in the RS_{pos} (0.017 ± 0.035). These suggested that an attractive serial dependence was in the speed estimation, which was not affected by the speed range.

Summary

In summary, the results of Experiment 1 demonstrated that the speed estimates were systematically biased towards the distribution center, showing a central tendency. Additionally, the current speed estimate was biased towards the previously presented speed, showing a serial dependence. Note that the central tendency was affected by the speed range. The faster the speed range is, the more central tendent the speed estimation is. In contrast, the serial dependence was not affected by the speed range.

Experiment 2 non-uniform distributions with the same range

Experiment 1 revealed central tendency and serial dependence in the speed estimation with three uniform distributions. In Experiment 2, we selected speeds in increasing, unform, and decreasing distributions to re-examine the findings of Experiment 1.

Methods

Participants

Twenty-four participants (14 females, 7 males, 19–25 years old) were recruited from Zhejiang Normal University. All were naïve to the experimental purpose and had normal or corrected-to-normal vision. The experiment was approved by the Scientific and Ethical Review Committee in the Department of Psychology of Zhejiang Normal University, which is in accordance with the Declaration of Helsinki.\.

Stimulus, apparatus, procedure, data analysis

These parameters were similar to those in Experiment 1, except that that (1) speeds were selected from the slow range: [0.88 deg/s, 6.15 deg/s] with a step of 0.66 deg/s; (2) Each participant finished three blocks with each corresponding to one distribution: increasing, uniform, and decreasing distributions. Table 1 lists the trial numbers of different speeds in different distributions. It is important to note that the centers of the three distributions were different (Right column in Table 1). The center of the increasing distribution is faster than that of the uniform distribution. In contrast, the center of the decreasing distribution is slower than that of the uniform distribution.

Results

Estimation bias

The linear fitting results were shown in Fig. 4 a. Black, red and blue dots show participants' performance in the increasing, uniform, and decreasing distributions. The linear functions explained more than 92.36% variances. Consistent with Experiment 1 (Fig. 2 a). In Fig. 4 a, the gray diagonal line indicates that the speed estimates are the same as the actual speeds, showing the perfect estimation (Fig. 1 d). The horizontal dashed lines indicate that the speed estimate is always the center of each distribution, showing an ideal central tendency (Fig. 1 d). Figure 3 a shows that the speed estimates are between the pure central tendency (dark dashed line) and the perfect estimation (gray dashed line), suggesting that the speed estimate is central tendent, consistent with Experiment 1.

Figure 4 b plots the slope (c) of the linear function against the three distributions. One sample t test showed that the slopes were all significantly smaller than 1 (Slow: Mean ± SD, 0.52 ± 0.33, $t(29) = -7.12$, $p<0.001$, Cohen's d = 2.97; Medium: 0.51 ± 0.27, $t(29) = -8.83$, $p<0.001$, Cohen's d = 3.68; Fast: 0.52 ± 0.23, $t(29)=-10.06$, $p<0.001$, Cohen's d = 4.20). These suggested that central tendency was in the speed estimation. Additionally, Fig. 4 b also shows that the slopes were not significantly different among the three distributions decreases with the increase of the speed range, which was confirmed by one-factor repeated measures ANOVA ($F(2,46)=0.027$, $p=0.97$, $\eta^2<0.001$). This suggested that the size of the

Table 1 Trial numbers of different speeds in three distributions

Distribution	Speed (deg/s)									
	0.88	**1.54**	**2.20**	**2.85**	**3.51**	**4.17**	**4.83**	**5.49**	**6.15**	**Distribution center**
Increasing	4	8	12	16	20	24	28	32	36	4.39
Uniform	20	20	20	20	20	20	20	20	20	3.51
Decreasing	36	32	28	24	20	16	12	8	4	2.63

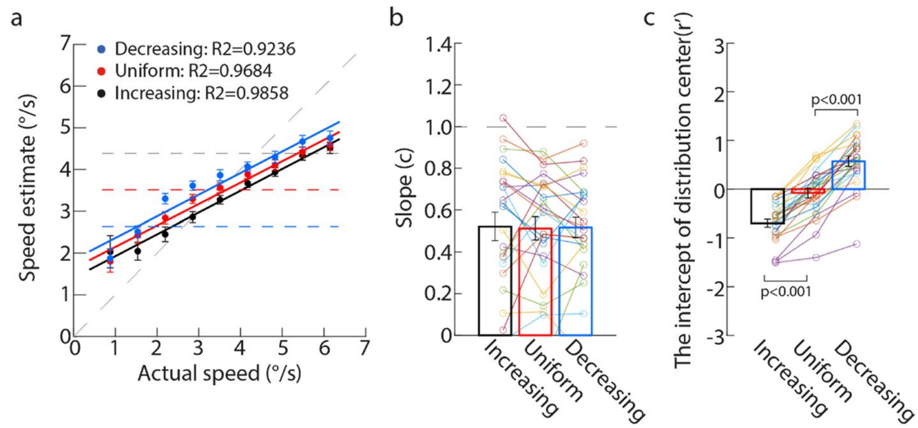

Fig. 4 Results of estimation bias in Experiment 2. **a** The speed estimate is against the actual speed. The black, red and blue dots correspond to the increasing, uniform, and decreasing distributions. Each dot indicates the mean speed estimate averaged across 24 participants. Error bars are the standard error across 24 participants. Solid lines are the best fitting results of Eq. 1. **b** and (**c**) plot the slope (**c**) and the intercept of distribution center (r', the difference between the speed estimate when the actual speed was the distribution center and the range center) against three distributions (increasing, uniform, and decreasing). Error bar is the standard error across 24 participants. Circles correspond to the participants' data

central tendency was maintained as long as the distribution range remained constant.

Figure 4 c plots the intercept of the distribution center (r') against the three distributions. One sample *t* test showed that the r' in the uniform distribution was not significantly different from 0 (-0.079 ± 0.50, $t(29)$ = -0.78, $p = 0.45$, Cohen's d = 0.32), suggesting that when the actual speed was the distribution center (3.51 deg/s), the speed estimate was equal to the distribution center, which was consistent with Experiment 1. In contrast, the r' in the increasing distribution was significantly smaller than 0 (Mean ± SD, -0.70 ± 0.40, $t(29)$ = -8.57, $p < 0.001$, Cohen's d = 3.57), meaning that when the actual speed was the distribution center (4.39 deg/s), the speed estimate was slower than the actual speed by 0.70 deg/s; the r' in the decreasing distribution was significantly larger than 0 (0.57 ± 0.53, $t(29) = 5.31$, $p < 0.001$, Cohen's d = 2.21), meaning that when the actual speed was the distribution center (2.63 deg/s), the speed estimate was faster than the actual speed by 0.57 deg/s.

As shown in Table 1, in comparison to the uniform distribution, there was a greater prevalence of fast speeds in the increasing distribution, while there was a greater prevalence of slow speeds in the decreasing distribution. These findings indicated that the speed estimates in the increasing and decreasing distributions were systematically biased away from the heavy side of the distributions.

Serial dependence

Figure 5 plots the results of serial dependence. It clearly shows that the corrected relative estimation error (CREE) when the speed of the previous 1st trial was slower than that of the current trial (RS_{neg}) was more negative than that when the speed of the previous 1st trial was faster than that of the current trial (RS_{pos}). This pattern is consistent with Experiment 1. A repeated measures ANOVA with the relative speed (RS_{neg} vs. RS_{pos}) and distributions (increasing, uniform, decreasing) as the within-subject factors showed that only the relative speed was significant ($F(1,23) = 37.03$, $p < 0.001$, $\eta^2 = 0.62$), and the CREE in the RS_{neg} (Mean ± SE: -0.092 ± 0.039) was more negative than that in the RS_{pos} (0.16 ± 0.032). These suggested that an attractive serial dependence was in the speed estimation, which was not affected by the speed distribution, consistent with Experiment 1.

Summary

In summary, Experiment 2 well replicated the central tendency and serial dependence revealed in Experiment 1. Importantly, the current experiment showed that the size of central tendency was constant as long as the distribution range was constant. Additionally, when the distribution was non-uniform, the speed estimates were biased away from the heavy tail of the distribution.

General discussion

In the current study, two experiments were conducted to examine the overall estimation bias (central tendency) and serial dependence in speed estimation. The results showed that the estimates of currently presented speeds were systematically compressed towards the center of the speed distribution, showing a central tendency that was modulated by the boundaries of speed ranges. Additionally, the estimates were also biased towards the previously presented speeds, showing an attractive serial dependence that was not affected by the speed

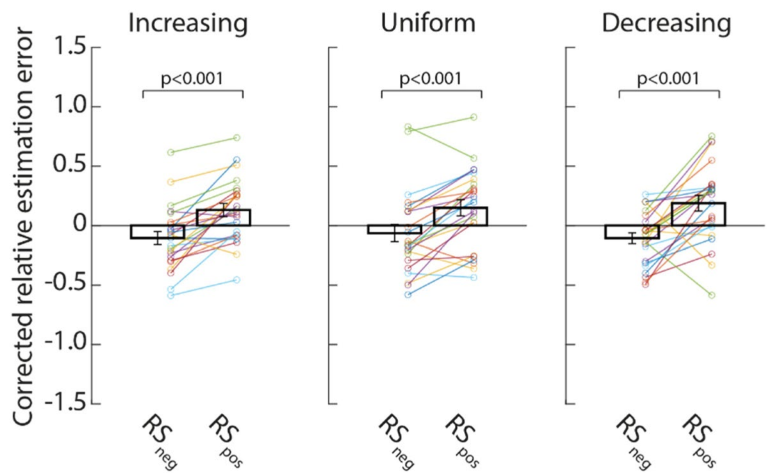

Fig. 5 Serial dependence results of Experiment 2. **a**–**c** correspond to the slow, moderate, and fast ranges. In each panel, the left and right bars correspond to the negative and positive relative speed (RS). The relative speed means the difference in the actual speed between the previous 1st trial and the current trial. RS_{neg} and RS_{pos} mean that the speed of the previous 1st trial is slower and faster than the speed of the current trial. Error bar is the corrected relative estimation error (CREE) across 24 participants. Circles correspond to the participants' data

distribution. Moreover, in comparison to the uniform distribution, the speed estimates were biased away from the heavy side of the distribution. In summary, the current study comprehensively reveals the estimation biases in speed estimation.

It has been demonstrated that a slow-speed bias is present in the speed estimation, with this bias increasing with the decrease in the luminance contrast [38, 40, 46]. The speeds presented in these studies were typically selected from a large range. When the speed range was narrowed, the slow-speed bias was no longer observed. In other words, the speed estimation bias (i.e., the difference between the estimated and actual speed) is affected by the range of speeds. Specifically, when the range of speeds is broad and includes very slow speeds (e.g., 0.5 deg/s in Stoker & Simoncelli, 2006), there is a slow-speed bias; whereas when the range is narrow and the speeds in the range tend to be fast, there is a central tendency.

Studies have also shown that the central tendency is also well aligned with the predictions of the Bayesian observer model [22, 34, 49], which indicates that the size of central tendency increases with the decrease in the certainty of features. Given that the discrimination sensitivity (i.e., certainty) of speeds decreases with the speed [39], it can be proposed that the increase in the size of the central tendency with the boundary of speed ranges is also consistent with the Bayesian inference account. Previous studies have posited that the effects of the luminance contrast on the slow-speed bias are consistent with the Bayesian observer model [15, 38], in which our sensory system has stored a long-term prior that includes large proportion of slow speeds. When the certainty of the speed (e.g., low luminance contrast) is decreased, observers will improve their reliance on the long-term prior and bias their speed estimates towards the slow speed. Given the Bayesian explanation for slow-speed bias and central tendency, it, therefore, can be believed that the speed estimation is a Bayesian decoding process.

These findings also suggest that the prior used to estimate speeds can be updated according to the experimental conditions. Some statistical learning studies have proposed that our visual system integrates the distributions of physical features learned in the experiment (short-term prior) and in the evolutionary process (long-term prior) to generate a new prior, which is then utilized to decode the feature value [1, 29, 38]. Accordingly, when the speed range is extensive and encompasses very slow speeds, the long-term prior is derived from the evolutionary process (i.e., the proportion of slow speeds is greater than that of fast speeds, Stocker & Simoncelli [38, 39], , which was integrated with the distribution of speeds learned in the experiment. However, there are still more slow speeds than fast speeds in the new prior. The Bayesian observer will show a slow-speed bias. In contrast, when the speed range is narrowed, the long-term prior will be corrected into a uniform distribution. This is because, in everyday life, speeds are typically maintained within a narrow range and remain stable for extended periods, such as walking, running, and driving. As a result, the new prior in the experiment is the integration of the corrected uniform long-term prior and the short-term prior. The Bayesian observer will show a central tendency. It should be noted that these are preliminary proposals, which may be subject to further examination in future studies.

The development of the aforementioned proposals can assist in elucidating the finding when the distribution of speed is non-uniform, and the speed estimates are biased away from the heavy tails of the distribution. It has been found that when the proportion of one feature in the feature distribution recently learned is higher than that in the distribution learned earlier, participants tend to bias their estimate away from the feature value. This phenomenon is referred to as the prevalence-induced concept change effect (PICC, Levari [24, 25, 42, 44], . Our proposal suggests that observers adjust their long-term prior to a uniform distribution that conflicts with their short-term prior (decreasing or increasing distribution), which biases the estimates away from the heavy tail of the short-term prior. This finding may indicate the presence of a PICC effect in speed estimation, which requires further investigation.

Additionally, researchers have conducted extensive studies to explore the serial dependence in various physical features [11, 26, 33], yet none of them have explored the serial dependence in speed perception. Our current study well addressed this gap in the literature and found the serial dependence in the speed estimation.

One popular question in the serial dependence is its computational mechanisms. Some studies have agreed that serial dependence is (partially) consistent with the Bayesian inference process (e.g., Cicchini et al., [10, 18, 50]. In particular, when the certainty of current features is decreased, observers will rely more on previous features [8, 18]. In the current study, we confirmed that when the speed range was increased, both the certainties of the previously and currently presented speeds were decreased. That is, the changes in the certainty were balanced between the previous and current speeds, which may lead to no effect of speed range on serial dependence [10]. Besides, Holland and Lockhead [20] proposed that observers could consciously remember the lastly presented feature and used it to modulate the following judgment, which led to the reduction or no significant difference in the estimation bias size and variances. Therefore, the negative results found in the current study could also be attributed to this proposal. In addition, previous studies also debated a lot on the occurrence mechanisms underlying serial dependence. That is, whether serial dependence is purely perceptual or the post-perceptual abilities were involved in (e.g., Bliss & D'Esposito, [4]; Ceylan et al., [8, 14, 17, 50]. Sun et al. [42, 44] found the stimulus distribution affected the serial dependence in self-motion direction perception and argued that post-perceptual abilities were involved in. In contrast, the speed distribution did not affect the serial dependence in the speed estimation, suggesting that the serial dependence maybe purely perceptual. Therefore, the occurrence mechanisms underlying serial dependence can be varied among the physical features, even as they all belong to the same category (e.g., dynamic feature). Anyway, the present study will contribute to the existing literature by investigating the underlying mechanisms of serial dependence in speed estimation.

Blonde´, Kristja´nsson, and Pascucci [6] found that a stronger serial dependence was observed when the temporal correlation in the stimulus features was weak, and as the temporal correlation was strong, the serial dependence would become a repulsion effect. Similar result pattern was also observed in Sun, Wang, & Gong [42], in which when the stimulus distribution was close to the natural distribution, there was a repulsion effect; in contrast, as the stimulus distribution was opposite to the natural distribution, there was an attractive serial dependence. This means that when the temporal stability of the stimulus was broken or the temporal distribution of features in the experiment conflicted with our previous experience, observers tended to keep stability or continuity across different stimuli, leading to attractive serial dependence. In Experiment 2, three distributions are all different from the natural speed distribution [39] and the conflicts between the distribution and natural distribution could be the same, the serial dependences, therefore, were not significantly different across different distributions. This proposal can also be further examined in future studies.

Moreover, as mentioned in Introduction, previous studies have argued that the central tendency and serial dependence can be the same effect [7, 19, 34, 48] and arise from a common underlying mechanism Tong et al., [47]. Or some even found that the two effects are positively correlated [19]; Sun, Zhang, Wang, Gong, & Dong, [41]. Actually, our data analysis method in which we took the estimation error of the current trial induced by the unpresented trial presented after the current trial as the baseline error, and used the estimate error induced by the previous trial to subtract the baseline error. Given the fact that an unpresented feature cannot affect the perception of the currently presented feature, it can be proposed that the residual estimation error is purely induced by serial dependence. Moreover, our data patterns in the two experiments have supported our proposal. If the central tendency was intertwined with the serial dependence, then as the central tendence is increased, the magnitude of serial dependence will be correspondingly increased; and when the estimation error is systematically biased towards one side (meaning that central tendence was modulated by speed distributions), then serial dependence will be also biased. However, Experiment 1 found the serial dependence was not significantly changed as the central tendency was increased; and Experiment 2 found that serial dependence was not affected by the speed distribution while central tendency was affected by the speed distribution. Furthermore, to further support our observation, we calculated the Pearson correlations between the estimation errors induced by central tendency and serial dependence in the two experiments. The results showed that none of the correlations was significant (ps > 0.10). Therefore, the central tendency and serial dependence were not the same effect or correlated with each other in the current study.

Apart from the aforementioned findings, we shall admit that the experimental design of the study (especially in Experiment 1) is flawed. Firstly, participants were asked to estimate speeds on a speed ruler with boundaries, which will inevitably lead to a range effect. Recently, Sun, Xu, and Stocker [43] demonstrated that the range of the response ruler affects the bias of feature estimation. In the current study, we proposed that participants were shown the same ruler in three sessions, which could balance the errors induced by the range effect. Additionally, in Experiment 2, the ruler range was shorter than in Experiment 1. Comparing the results of the same conditions Experiments 1 (slow) and 2 (uniform) showed that the slope of Experiment 1 tended to be larger than that in Experiment 2 (dark maker in Fig. 2 and red marker in Fig. 4) (Repeated Measures ANOVA showed that the main effect of the two experiment was marginally significant ($F(1, 52) = 3.71$, $p = 0.052$, $\eta2 = 0.067$)), suggesting that the response boundary could affect the speed estimation. However, due to the different experimental conditions in the two experiments, the robustness of the above result remains to be further tested. Moreover, to rule out the range effect, the most direct method is to ask participants to conduct a two-alternative forced choice (2AFC) task, which generates a psychometric function and then determines the bias. However, this method necessitates a considerable number of trials, rendering it ineffective. Consequently, researchers must develop a novel method to assess the efficacy of the findings in the current study.

Secondly, as mentioned in Introduction, studies have demonstrated that the central tendency is consistent with the Bayesian inference process (e.g., Ashourian & Loewenstein [3, 22, 30, 31], and the discrimination sensitivity of speeds is decrease with the increase of speeds [39]. When the certainty (discrimination sensitivity) of physical features is decreased, the estimate will be biased more towards the range center. That is, when the speeds increase with a constant step/delta, the certainty or discrimination sensitivity of the speed does not linearly increase. Consequently, it will be more likely that a nonlinear relationship between the speed estimate and the actual speed. As in Sun, Xu, and Stocker [43], they found that the larger the response range is, the lower central tendency is. In the three conditions of Experiment 1, the subjective/internal-represented response range could be also varied among conditions. Therefore, the linear finding of the current study can be a confounded results of the task difficulty and speed ruler, and so on. Future studies can be considered to dissociate the effects of the task difficulty, speed ruler, and discrimination sensitivity on the speed processing.

In summary, the current study explored the estimation bias and serial dependence in speed estimation with two behavioral experiments. We also made some explanations for these findings, which may provide some research inspiration for other researchers.

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Authors' contributions
SYW collected the data; XYZ proof-read and reviewed the manuscript. QS proposed the idea, analyzed the data, wrote and edited the manuscript.

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Data availability
Now the data have been uploaded on OSF https://osf.io/y7vjw/?view_only=70719b0e33f2471eadd410115ccb2c53. The data will be open access when the paper is accepted.

Declarations

Ethics approval and consent to participate
We confirm that all methods were carried out in accordance with relevant guidelines and regulations. We confirm that informed consent has been obtained from all participants in this research. Ethical approval for this study was obtained from the Scientific and Ethical Review Committee in the Department of Psychology of Zhejiang Normal University.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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