

Not all fixations are created equal: The benefits of using ex-Gaussian modeling of fixation durations

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Various cognitive and perceptual factors have been shown to modulate the duration of fixations during visual exploration of complex scenes. The majority of these studies have only considered the mean of the distribution of fixation durations. However, this distribution is skewed to the right, so that an increase in the mean may be driven by a lengthening of all fixations (i.e., a right shift of the whole distribution) or only the relatively longer ones (i.e., a longer right tail of the distribution). To determine which factor is at play, the distribution can be modeled with an ex-Gaussian distribution, which is a convolution of a Gaussian and an exponential distribution. Here we demonstrate the usefulness of applying the ex-Gaussian model to empirical distributions of fixation durations and the reliability of its parameters across time. We demonstrate how the ex-Gaussian model had advantages over exclusive consideration of the mean, by showing that an increase in the mean can stem from specific changes in the components of the ex-Gaussian distribution. Specifically, the type of image leads to a change in the Gaussian component alone, indicating a right shift of the main mass of the distribution. By contrast, familiarity with the inspected image modifies the exponential component, and results in a more specific modulation of a subset of relatively long fixations. Hence, estimating the ex-Gaussian parameters may provide novel insights into the underlying processes that determine fixation duration and can contribute to the future development of process-based computational models of gaze behavior.

Introduction

Vision is an active process in which viewers continuously select where and when to move their gaze. By shifting the locus of gaze approximately three times a second, viewers select which visual information will be processed by the high-resolution center of the retina (i.e., the fovea) and for how long. Early studies of complex scene viewing (Buswell, 1935; Yarbus, 1967) examined how gaze position is influenced by instructions to observers and their level of expertise. More recent studies have expanded on these findings by examining how low-level features of visual input (e.g., Foulsham & Underwood, 2008; Itti, 2005; ; Itti & Koch, 2000; Itti, Koch, & Niebur, 1998; Parkhurst, Law, & Niebur, 2002) and high-level observer factors (e.g., De Haas, Iakovidis, Schwarzkopf, & Gegenfurtner, 2019; Guy et al., 2019) modify where gaze is directed. In addition to this stream of works, which has focused on the spatial characteristics of fixations, other studies have aimed to decipher the underlying processes that determine the temporal aspect of fixations; that is, how long gaze remains relatively stable before it is shifted to a new location (i.e., fixation duration). These studies have shown that fixation durations are sensitive to different factors such as changes in the luminance of the image (Henderson, Nuthmann, & Luke, 2013), the image type (Kaspar & König, 2011), the characteristics of next saccade (Unema, Pannasch, Joos, & Velichkovsky, 2005), the task at hand (Nuthmann, 2017), and memory (Althoff & Cohen, 1999; Schwedes & Wentura, 2016). Although massively contributing to the literature on the factors influencing fixation duration, most of these works have used the

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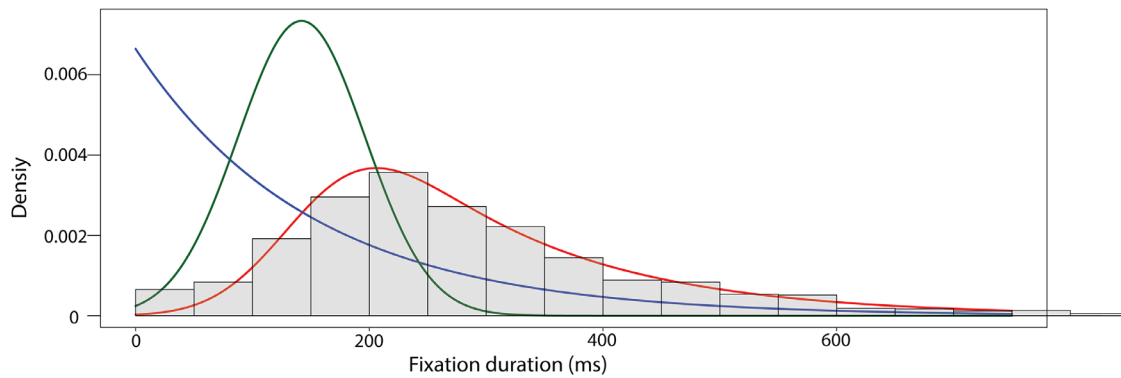


Figure 1. Histogram of fixation durations of one participant from dataset 1. The ex-Gaussian fit is shown in red, the Gaussian component (defined by μ and σ) in green and the exponential (defined by τ) in blue.

mean as a summary statistic for the distribution of fixation durations. Here, we posited that this approach may mask the actual nature of these distributions, because an increase in the mean can result from at least two different modifications of the distribution: either an overall shift of the whole distribution, or lengthening of only some of the fixations. Because an analysis restricted to the mean cannot differentiate between the two, we sought to determine whether another statistical method could better characterize differences in the shape of the distribution of fixation durations.

Inspired by manual reaction time research (Balota & Yap, 2011; Shahar, Teodorescu, Usher, Pereg, & Meiran, 2014), studies of gaze behavior during reading have offered a solution to this issue by modeling the distribution of fixation durations. For that purpose, these studies used the ex-Gaussian distribution, which is a convolution of Gaussian and exponential distributions. This distribution, as well as the empirical distribution of fixation durations, are skewed to the right. Three parameters define this distribution: μ and σ , which are the parameters of the Gaussian distribution and τ , which is the parameter of the exponential distribution (Figure 1). In reading, different lexical factors have been found to relate to specific modifications of the ex-Gaussian components. For example, more predictable words (Staub, 2011) and less lexical ambiguity (Sheridan & Reingold, 2012) were found to be associated with a left shift of the Gaussian component of the distribution; that is, smaller μ values. Other studies have revealed that some factors influence both the Gaussian and the exponential components, such as word frequency (Staub, White, Drieghe, Hollway, & Rayner, 2010) or whether the word is visible in the parafovea before fixating on it (Reingold, Reichle, Glaholt, & Sheridan, 2012). The existence of different distributional modulation for these two factors (e.g., word frequency and word predictability) would suggest that there is a substantial difference between the processes associated with each factor, and could

potentially drive other, more informative, process-based models.

However, only a handful of studies have used this statistical technique to characterize the fixation duration distribution during the visual exploration of scenes. To the best of our knowledge, the first study to apply this method to scene viewing dealt primarily with saccades and microsaccades, and examined whether they shared the same generator (Otero-Millan, Troncoso, Macknik, Serrano-Pedraza, & Martinez-Conde, 2008). The findings showed that, in both saccades and microsaccades, the μ values of the fixation duration distribution were related to the magnitude of the next saccadic displacement, suggesting a common generator for both movements. Even though more than a decade passed since the publication of this report, it was followed by only a few other studies, which focused mainly on the modification of fixation durations owing to changes of the visual input (flipping and spatial filtering: Glaholt & Reingold, 2012; masking: Luke, Nuthmann, & Henderson, 2013; and luminance: Calen Walshe & Nuthmann, 2014). These studies indicated that an abrupt modification of the stimulus during viewing extended the durations of the subsequent fixations. Specifically, stimulus changes were associated with larger μ and σ values (i.e., a right shift of the Gaussian component) compared with the no-change condition. Moreover, the τ values only increased when substantial modifications were made to the dataset (e.g., low-pass filtering and major luminance reduction). A change of τ was also apparent when participants observed blurred rather than unmodified images (Luke & Henderson, 2016).

Although these studies are sparse, they provide initial evidence for the benefits of ex-Gaussian modeling of fixation durations. Specifically, using ex-Gaussian parameters may lead to a better understanding of the processes that underlie visual exploration (Luke, Smith, Schmidt, & Henderson, 2014) and cognitive mechanisms in general (Luke, Darowski, & Gale, 2018).

For example, [Luke et al. \(2018\)](#) examined the relationship between individuals' fixation duration distribution and working memory span (measured by operation, symmetric, and reading span tasks). Participants performed a working memory task, viewed scenes, and read text. The fixation duration distribution during scene viewing was fitted to an ex-Gaussian distribution, indicating lower τ values (smaller tail) and larger μ values for participants with larger working memory spans. These relationships between the ex-Gaussian parameters and working memory span could reflect two underlying processes that support better memory span. First, the increase in the tail of the distribution might reflect lapses of attention, which are less frequent in individuals with higher spans ([McVay & Kane, 2012](#)). Thus, relatively long fixations (captured in the tail component) could reflect attentional processes involved in working memory performance. Second, the positive relationship between μ and working memory span could indicate that individuals with larger working memory spans typically have longer fixations than individuals with smaller spans. This factor might be due to their effort to extract and retain more information during each fixation. Importantly, this study showed that the working memory span has a complex relationship with fixation duration; individuals with higher spans had longer fixations in general (as indicated by the higher μ), but also had fewer relatively long fixations (as indicated by lower values of τ). Thus, this effect could have been missed if they had only used the mean fixation duration instead of the ex-Gaussian parameters (i.e., the lengthening of most fixations might cancel out the lower number of relatively long fixations). Taken together, this study demonstrates how the use of ex-Gaussian parameters can reveal unknown relationships between gaze behavior and broader cognitive processes, which may serve to formulate new working hypotheses as to the mechanisms underlying these processes.

Beyond these contributions of the ex-Gaussian modeling to cognitive research, this method has two other important advantages for eye tracking studies of scene viewing. Estimating the ex-Gaussian parameters can pave the way for future studies by highlighting the subgroup of fixations that are sensitive to the nature of the manipulation: an effect of μ would indicate a general effect on most fixations, whereas an effect of τ would indicate a change in long fixations alone ([Balota & Yap, 2011](#)). Second, using the statistical tool of ex-Gaussian modeling can guide process-oriented models that aim to describe the mechanisms determining fixation duration and visual exploration in general. The litmus test of these models is their ability to explain reported effects in the field of visual exploration. By identifying the factors influencing specific parameters of the ex-Gaussian distribution, the distribution of fixation duration can be better characterized and enable models to predict

these distributional changes beyond those of the mean (e.g., [Nuthmann, Smith, Engbert, & Henderson, 2010](#)). This will help models to describe more fine-grained characteristics of the empirical findings and enhance their overall contribution.

The overarching goal of this article is thus to provide a framework for the use of ex-Gaussian modeling in scene viewing studies by relating to both theoretical and practical aspects of this approach. We start by showing that the ex-Gaussian model faithfully describes the empirical fixation duration distribution. Then, we explore whether the modeled ex-Gaussian distribution of fixation durations varies across individuals in a reliable manner. To do so, we examine the distributions of fixation durations of the same individuals in two different sessions, recorded 1 week apart. Finally, we demonstrate how modulation of the mean fixation duration, the most common measure used in the scene viewing literature, can reflect two different changes in the distribution. By reanalyzing published studies that have solely addressed the mean fixation duration, we show that the exploration of natural images, in comparison with urban images, lead to a right shift of the Gaussian component (as indicated by higher μ values), whereas familiarity with the stimuli lead to a longer tail of the exponential component (as indicated by larger τ values). To make all these analyses more accessible, we also provide the scripts for computing the ex-Gaussian analysis.¹

Methods

Datasets

We used three different datasets of participants' gaze behavior during scene observation. The first dataset was collected from two different sessions and was used to evaluate the reliability of the model parameters over time. The other two datasets were taken from published studies in which the mean fixation duration was reported to reflect changes in cognitive processes. Therefore, the data from these studies could be used to examine whether the reported mean fixation duration effects would manifest in different parameters of the ex-Gaussian distribution. In what follows, we provide a brief description of the aims, methods, and results of the studies that motivated the collection of each dataset.

Dataset 1: Reliability over time

This dataset comprises gaze samples from an experiment consisting of two sessions, recorded 7 days apart. Forty-two participants took part in the first session and 37 returned for the second session. In each

session, participants completed a free viewing task. Images were presented for 3 seconds on a monitor with a 1024×768 screen resolution, corresponding with a screen size of $56.0^\circ \times 33.5^\circ$ of visual angle, situated at a distance of 50 cm. Monocular gaze position was tracked at 1000 Hz with an Eyelink 1000 (SR Research Ltd., Mississauga, Ontario, Canada). The data were originally collected to examine the reliability of various eye movement measures (e.g., mean fixation duration) over time. The correlation between the mean fixation duration in session 1 and session 2 was highly significant, $r = 0.82$, $p < 0.0001$, replicating previous studies (Guy et al., 2019; Henderson & Luke, 2014).

Dataset 2: Different types of images

This dataset includes data from three experiments taken from an open database (Wilming et al., 2017). Overall, the dataset is composed of gaze samples of 118 observers (48, 47, and 23² participants in experiments 1, 2, and 3, respectively). In all the experiments, participants were asked to freely view a set of images from different categories (natural, urban, fractal, pink noise). The images were displayed on a monitor with a 1280×960 screen resolution, corresponding with a screen size of $29^\circ \times 22^\circ$, $35^\circ \times 26.5^\circ$, and $28^\circ \times 21^\circ$, at a distance of 80, 65, and 80 cm for experiments 1, 2, and 3, respectively. Each image was presented for 6 seconds in the first and third experiments, and for 5 seconds in the second experiment. Monocular gaze position was tracked at 500 Hz with an Eyelink 2 (experiment 1 and 3) and Eyelink 1000 (experiment 2; SR Research Ltd.).

The three experiments were designed to explore different aspects of gaze behavior during the inspection of complex images. The first experiment examined how gaze behavior is modified by the type of the image (e.g., natural vs. urban). The two other experiments investigated how the effect interacts with the handedness of the observer (experiment 2) and age (experiment 3). All the experiments involved the inspection of natural and urban images, which have been shown to elicit different patterns of fixation durations (Kaspar et al., 2013). Specifically, the inspection of natural images is accompanied by longer fixations, on average, than urban images.

Dataset 3: Repetitive displays

This dataset comprised three experiments. The first two experiments have been published elsewhere (Lancry-Dayana, Kupersmidt, & Pertzov, 2019). Note that the original study included another experiment that was excluded here because of a problem in its design (also reported in the original article). However, the results of this experiment are consistent with the

other experiments, as discussed in the Supplementary Materials. In addition, this dataset includes another experiment, which is reported here for the first time. Overall, gaze samples from 96 observers (30, 35, and 31 participants in experiments 1, 2, and 3, respectively) made up this dataset. The stimuli were displayed on a monitor with a 1024×768 screen resolution, corresponding with a screen size of $46.5^\circ \times 27.0^\circ$, situated at a distance of 60 cm. Monocular gaze position was tracked at 1000 Hz with an Eyelink 1000+ (SR Research Ltd.).

The goal of these experiments was to examine changes in gaze behavior across repetitive exposures to the same set of images during a memory encoding task (experiment 1 and experiment 2) and free viewing (experiment 3). In each experiment, participants were asked to view a set of images, each of which was presented for 5 seconds. In the first and second experiments, participants were told that the viewing phase would be followed by a memory test. In all experiments, the same set of images (experiment 1, 40 images, experiments 2 and 3, 20 images) was repetitively presented across separate blocks (experiment 1, four blocks; experiments 2 and 3, three blocks). In the second and third experiments, each block included another set of novel images, which was interleaved between blocks and was counterbalanced across participants. These sets were included to isolate the effect of familiarity from other possible effects resulting from repetitive exposures (e.g., fatigue). Finally, although the first experiment included four blocks, for comparability we only included the first three blocks in the analysis.

Overall, the previous study (Lancry-Dayana et al., 2019) reported a similar pattern of results in all experiments: as the images became more familiar across repetitive exposures, the mean fixation duration increased significantly. In the second and third experiments, these findings were only observed for the repeated images (and not for the novel images that changed on each block), thus strengthening the claim that familiarity is likely to be the cause of the prolonged fixations.

Data exclusion criteria

Based on the exclusion criteria implemented in previous studies on scene viewing (Calen Walshe & Nuthmann, 2014; Luke & Henderson, 2016), we excluded fixations shorter than 50 ms and longer than 1200 ms. This procedure resulted in the exclusion of 2.13% of the fixations (reliability across time dataset, 3.59%; different types of images dataset, 1.62%; repetitive displays dataset, 2.15%). We excluded participants with estimated parameters above/below the mean ± 3 standard deviations. This led to the exclusion of three participants out of 251.

Modeled distributions

Fitting the modeled distribution

We fitted the distribution of fixation durations of each participant to an ex-Gaussian distribution (convolution of an independent Gaussian and an exponential distribution) with three free parameters: (1) μ – the expected value of the Gaussian distribution, (2) σ – the standard deviation of the Gaussian distribution, and (3) τ – the scale parameter of the exponential distribution. We used the built-in function *timefit* from the *retimes* package of R to estimate the values of the μ , τ , and τ parameters for each distribution of fixation's durations. The *timefit* function uses maximum likelihood values to estimate the ex-Gaussian parameters. As an optimization function, we used the simplex method (Nelder & Mead, 1965), the default option of the *timefit* function. For further information on *timefit* see the “retimes” package in R (Massidda, 2013).

The fitting of the model was carried out separately for each participant and each condition of the different datasets:

- (1) *Reliability across time dataset.* The experiment in this dataset included two sessions in which participants were asked to freely view images of scenes. Thus, two ex-Gaussian distributions were fitted for each participant, once for each session.
- (2) *Different types of images dataset.* In this dataset, gaze position was recorded when participants inspected natural and urban scenes. Accordingly, for each of the three experiments in this dataset, we fitted the ex-Gaussian model twice for each participant, once for natural scenes and once for the urban scenes.
- (3) *Repetitive displays dataset.* In the experiments that composed this dataset, participants saw the same set of images in three blocks. Accordingly, we fitted an ex-Gaussian model for each block. In addition, in the second and third experiments, participants also saw a set of novel images in each block. Thus, in these experiments the fixations of the novel images were fitted separately from those of the repeating images. Taken together, we fitted three models per participant (one for each block) in the first experiment, and six models per participant (according to block, separately for repeating and novel images) in the second and third experiments.

Data analysis

Evaluation of the model

Goodness of fit

To evaluate the goodness of fit of the ex-Gaussian distribution to the data, we examined the fit in two

ways. The first was to test whether the ex-Gaussian distribution described the data better than a Gaussian distribution alone (which is often assumed to be the distribution, even if implicitly). Accordingly, we used a Bayesian information criterion (BIC) to compare the fit of the ex-Gaussian distribution to the fit of the Gaussian distribution. The BIC is a common criterion for model selection that takes into account both the goodness of fit of the model (as assessed by the likelihood function) and the threat of overfitting (as assessed by a penalty according to the number of parameters).

The second evaluation involved examining the congruency between the empirical distribution of fixation durations to the modeled ex-Gaussian distribution (i.e., the distribution obtained for the estimated parameters). To do so, we derived a random sample from the modeled ex-Gaussian distribution of the same size as the empirical distribution. We used two methods to examine the hypothesis that the simulated and empirical samples originated from the same distribution. A significant result would suggest that this hypothesis should be rejected, indicating that the two samples come from different distributions. First, we used the Kolmogorov–Smirnov test (with $\alpha = 0.05$). Because this procedure has a random component to account for sampling from the modeled distribution, we repeated this procedure 1,000 times and calculated the mean p value of the Kolmogorov–Smirnov tests. Additionally, consistent with the overall maximum likelihood approach we added another goodness of fit test, the empirical likelihood goodness of fit (Gurevich & Vexler, 2011), by using the R-package “dbEmpLikeGOF” (Miecznikowski, Vexler, & Shepherd, 2013). This test is based on the likelihood ratios of the two distributions and the p value is calculated using a Monte Carlo procedure (for further details see Miecznikowski et al., 2013). We ran this test in the same manner as the Kolmogorov–Smirnov test, with 100 repetitions and 100 samples from the empirical and modeled distributions (lower values are due to the extended running time of this procedure) and calculated the mean p value across all repetitions. Based on previous research on combining the p values of multiple dependent tests (Vovk & Wang, 2012), we multiplied the mean p value by 2 for both the Kolmogorov–Smirnov and the empirical likelihood goodness of fit methods. A mean p value larger than the α was considered as an indication that the empirical distribution was not significantly different from the modeled one and was a good fit. In the main text, we report the number of models that were not classified as poor fits out of the total number of models fitted for each experiment.

Correlations between parameters

The advantage of using ex-Gaussian modeling instead of the mean fixation duration is that modeling provides more parameters of the distribution and

therefore a richer description. However, having more parameters is only useful if they reflect different aspects of the mechanisms that generate the distribution. That is, if two parameters are highly correlated, it implies that they may reflect the same mechanism and therefore should be addressed as a single factor. In contrast, failing to find such correlations would indicate that the parameters may at least partially be related to different mechanisms. Although theoretically the parameters are independent, it is possible that dependencies can occur in the empirical data of fixation durations. Therefore, we calculated the correlations between the different parameters within each model to assess for statistically independent (uncorrelated) parameters. Owing to the large number of models, in the main text we report the mean value of these correlations calculated separately for each of the experiments and conditions. To assess the statistical significance of the correlation results, we first applied Fisher's z transformation to the correlation coefficients (thereby converting the correlation coefficient values into a normally distributed variable amenable to parametric statistical testing) and then conducted one sample t tests to assess whether the correlations were significantly different than zero.

Reliability of the parameters

In addition to the cross-subject correlations between the model parameters, we also examined to what extent these parameters were reliable over time. This issue is more than a technicality related to the fitting of the model, but rather reflects to what extent the model parameters characterize stable gaze characteristics of the observer. The reliability of a measure is often regarded as a prerequisite for a meaningful examination in the cognitive sciences: if a measure is not reliable, it will result in different values under the same conditions and will be less informative for research. Specifically, we examined whether the model parameters were a credible characteristic of the observer, beyond any possible momentary effects. To do so, we calculated the test–retest correlations between gaze behavior parameters that were collected on two different sessions (1 week apart) under similar conditions.

Reanalyzing data: The ex-Gaussian parameters versus the mean fixation duration

After evaluating the quality of the model and the relationships among its parameters, we analyzed how different manipulations affected these parameters. This analysis provides insights into changes in fixation durations distributions related to different cognitive factors. Importantly, previous attempts to characterize these modifications have focused on changes in the mean fixation duration in different conditions. The aim of this analysis was to examine how these reported

effects on the mean of the distribution are manifested in the different parameters of the distribution, and whether ex-Gaussian modeling could provide further insights that fail to be captured when exclusively analyzing the mean.

Different types of images dataset

Longer fixations, on average, were associated with the observation of natural as compared with urban images. To assess whether image type had an influence on specific parameters of the ex-Gaussian distribution we conducted a one-way analysis of variance (ANOVA) with image type (natural/urban) as the within-subjects factor, separately for each parameter.

Repetitive displays dataset

To determine whether specific parameters of the ex-Gaussian distribution changed across repetitive exposures, we carried out a one-way ANOVA with block (1/2/3) as the within factor separately for each parameter. Because each block in the second and third experiments included a set of novel images in addition to the set of repeating images, we conducted this analysis twice for each of these experiments: once for the repeating images and once for the changing ones.

Quantiles analysis

To further illustrate the relationship between changes in the estimated parameters and changes in the empirical distribution of the fixation durations, we plotted a quantile graph for the different conditions of each dataset (see Balota & Yap, 2011 for a similar analysis). Specifically, for the different types of images datasets we contrasted the natural and urban conditions, and in the repetitive displays dataset we contrasted the two extreme conditions, the first block and the third block. For each condition, we calculated the mean fixation duration of each decile. We carried out a paired t test (different types of images dataset: natural vs. urban; repetitive displays dataset: first block vs. third block) to determine which differences between the conditions were statistically significant.

Results

Evaluation of the model

Goodness of fit

In each experiment, an ex-Gaussian distribution was fitted to the distribution of fixation durations of each participant. In all experiments the ex-Gaussian distribution exhibited better goodness-of-fit than the

Dataset	Experiment	BIC ex-Gaussian	BIC Gaussian
Reliability over time	Experiment 1	24,924 (9,337)	25,895 (9,765)
Different types of images	Experiment 1	13,732 (1,912)	14,165 (1,986)
	Experiment 2	3,760 (588)	3,897 (606)
	Experiment 3	5,903 (709)	6,111 (742)
Repetitive displays	Experiment 1	7,092 (1,338)	7,333 (1,357)
	Experiment 2	3,846 (502)	3,967 (502)
	Experiment 3	3,414 (483)	3,543 (497)

Table 1. Means and standard deviations of BIC scores across individuals, for each experiment, for the ex-Gaussian and the Gaussian models.

Dataset and experiment	r values		
	Tau–Mu	Tau–Sigma	Mu–Sigma*
Stability over time			
Experiment 1	Ses1: $r(39) = -0.3$ Ses2: $r(34) = -0.09$	Ses1: $r(39) = -0.05$ Ses2: $r(34) = 0.13$	Ses1: $r(39) = 0.73$ Ses2: $r(34) = 0.68$
Different types of images			
Experiment 1	$r(45) = 0.15$	$r(45) = 0.23$	$r(45) = 0.75$
Experiment 2	$r(43) = -0.06$	$r(43) = 0.04$	$r(43) = 0.61$
Experiment 3	$r(21) = 0.02$	$r(21) = 0.11$	$r(21) = 0.56$
Repetitive displays			
Experiment 1	$r(28) = -0.17$	$r(28) = 0.06$	$r(28) = 0.78$
Experiment 2	$r(33) = -0.33$	$r(33) = 0.01$	$r(33) = 0.69$
Experiment 3	$r(29) = -0.02$	$r(29) = 0.01$	$r(29) = 0.84$

Table 2. Correlations between parameters in each session (first dataset) and condition (second and third datasets). *Notes:* For each experiment, we present the mean correlation across all ex-Gaussian models that were fitted separately for each participant and condition. Only the mean correlation between μ and σ was significantly different from zero, as indicated by an asterisk.

Gaussian distribution, as indicated by lower BIC scores (Table 1).

In addition, we examined the congruency between the empirical and the fitted ex-Gaussian distributions (for further details, see the Methods). Almost none of the fitting procedures led to significantly different distributions on the Kolmogorov–Smirnov test (overall, 5/795; reliability across time dataset, 3/77; different types of images dataset, 2/232; repetitive displays dataset, 0/486) and the empirical likelihood (overall, 0/795), indicating an adequate fit between the empirical and modeled distributions. For illustrations of the best and worst fits, see the Supplementary Materials.

Correlations between parameters

To assess the dependency between the parameters of the ex-Gaussian distribution, we examined the correlations between the different parameters in each session or condition (Table 2). Then, to examine whether the relationship between parameters was significant across experiments, for each two parameters, we conducted a two-tailed student t -test after

performing a Fisher transformation. This showed that the relationship between μ and σ was significantly higher than zero, $t(6) = 11.746$, $p < 0.0001$. The other relationships were not significantly different from zero, τ and σ : $t(6) = 2.366$, $p = 0.056$; τ and μ : $t(6) = -1.403$, $p = 0.21$. Therefore, although there was a strong positive correlation between the two parameters of the Gaussian distribution (μ and σ), the scaling parameter of the exponential distribution (τ) was weakly correlated with the other parameters (note that there was not even a consensus across experiments in the sign of these correlations).

Reliability of the parameters

To examine whether the parameters of the ex-Gaussian reflected a stable characteristic of the observer, we calculated the correlations between the same parameters across two different sessions. These correlations demonstrated high reliability of the parameters: τ , $r = 0.8$, $p < 0.0001$; μ $r = 0.81$, $p < 0.0001$, and σ , $r = 0.8$, $p < 0.0001$, suggesting that the parameters captured a reliable trait of visual

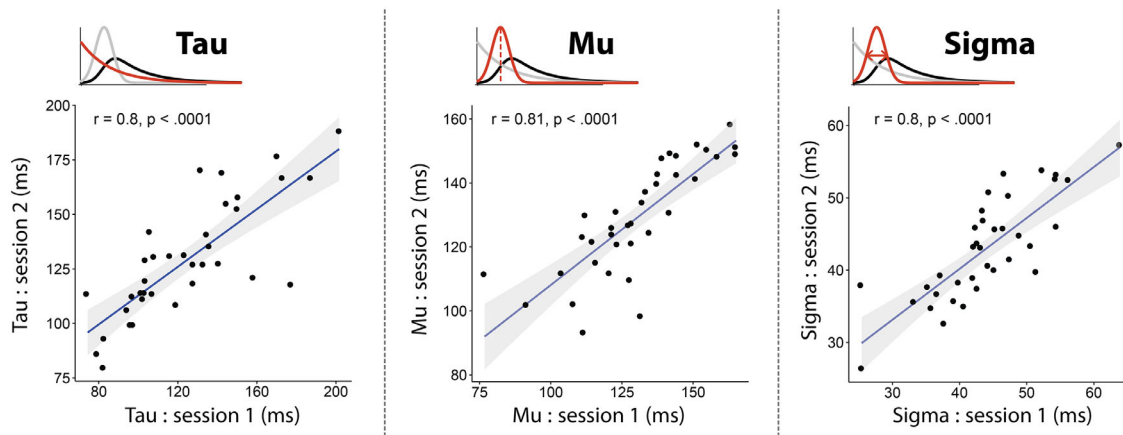


Figure 2. Scatter plots, regression lines and confidence intervals between individuals' ex-Gaussian parameters in the first and second sessions of the reliability over time dataset (x-axis and y-axis, respectively).

exploration behavior (Figure 2). Note that the sessions took place 1 week apart, indicating a persistence of the parameters over relatively long periods of time.

The ex-Gaussian parameters versus the mean fixation duration

Here, we reanalyzed data from published studies that used the mean fixation duration as a proxy for fixation duration behavior. Unlike the original studies, we considered the ex-Gaussian parameters instead of the mean fixation duration. We show how differences in the mean fixation duration can reflect distinct modifications of the distribution of fixation durations; specifically, these differences are suggested to stem from an overall shift of the main mass of the distribution (manifested in changes of μ), a modification of the tail (manifested in changes of τ) or a combination of both.

Image type as example of μ modulation

All the experiments in this dataset showed that exploration of natural images was accompanied, on average, by longer fixations in comparison with urban images. We examined whether using the ex-Gaussian parameters, which describe the distribution more precisely, would provide additional insights. We conducted a one-way ANOVA with image-type (natural/urban) as the within-subject factor, separately for each estimated parameter. Higher μ values were observed in fixations on natural images compared with urban images, experiment 1: $F(1, 47) = 78.289, p < 0.0001, R^2 = 0.113$; experiment 2: $F(1, 44) = 60.209, p < 0.0001, R^2 = 0.141$; experiment 3: $F(1, 22) = 43.357, p < 0.0001, R^2 = 0.186$. The same pattern was observed for the σ parameter, experiment 1: $F(1, 47)$

$= 127.82, p < 0.0001, R^2 = 0.216$; experiment 2: $F(1, 44) = 51.033, p < 0.0001, R^2 = 0.189$; experiment 3: $F(1, 22) = 22.912, p < 0.0001, R^2 = 0.12$. However, the τ parameter did not differ significantly between image types, experiment 1: $F(1, 47) = 1.634, p = 0.207, R^2 = 0.005$; experiment 2: $F(1, 44) = 1.333, p = 0.25, R^2 = 0.004$; experiment 3: $F(1, 22) = 2.495, p = 0.129, R^2 = 0.01$. Moreover, the change in the values of τ according to image type was not consistent across experiments; whereas in the first and third experiments the τ values were slightly higher in the natural condition, in the second experiment higher τ values were observed in the urban condition (Figure 3). Finding higher values of μ and σ without any significant effect of τ suggests that the original effect of mean fixation duration derived from a right shift of the Gaussian component of the distribution. Therefore, the impact of different types of images on fixation durations may be global, causing a change in the duration of the majority of fixations and not a specific change in only a small number of fixations.

Repeated displays as example of τ modulation

The three experiments in this dataset showed that mean fixation duration increased across repetitive displays of the same images. This effect vanished when the set of images changed between blocks, indicating that the increase in the mean fixation duration can be attributed to familiarity. We report a reanalysis of the same data by fitting an ex-Gaussian distribution for each participant in each block. For each parameter, we conducted a one-way ANOVA with block as the within-subject factor. Similar to the original work, in the second and third experiments, which included a set of novel images in each block, we conducted an additional one-way ANOVA for novel images. As

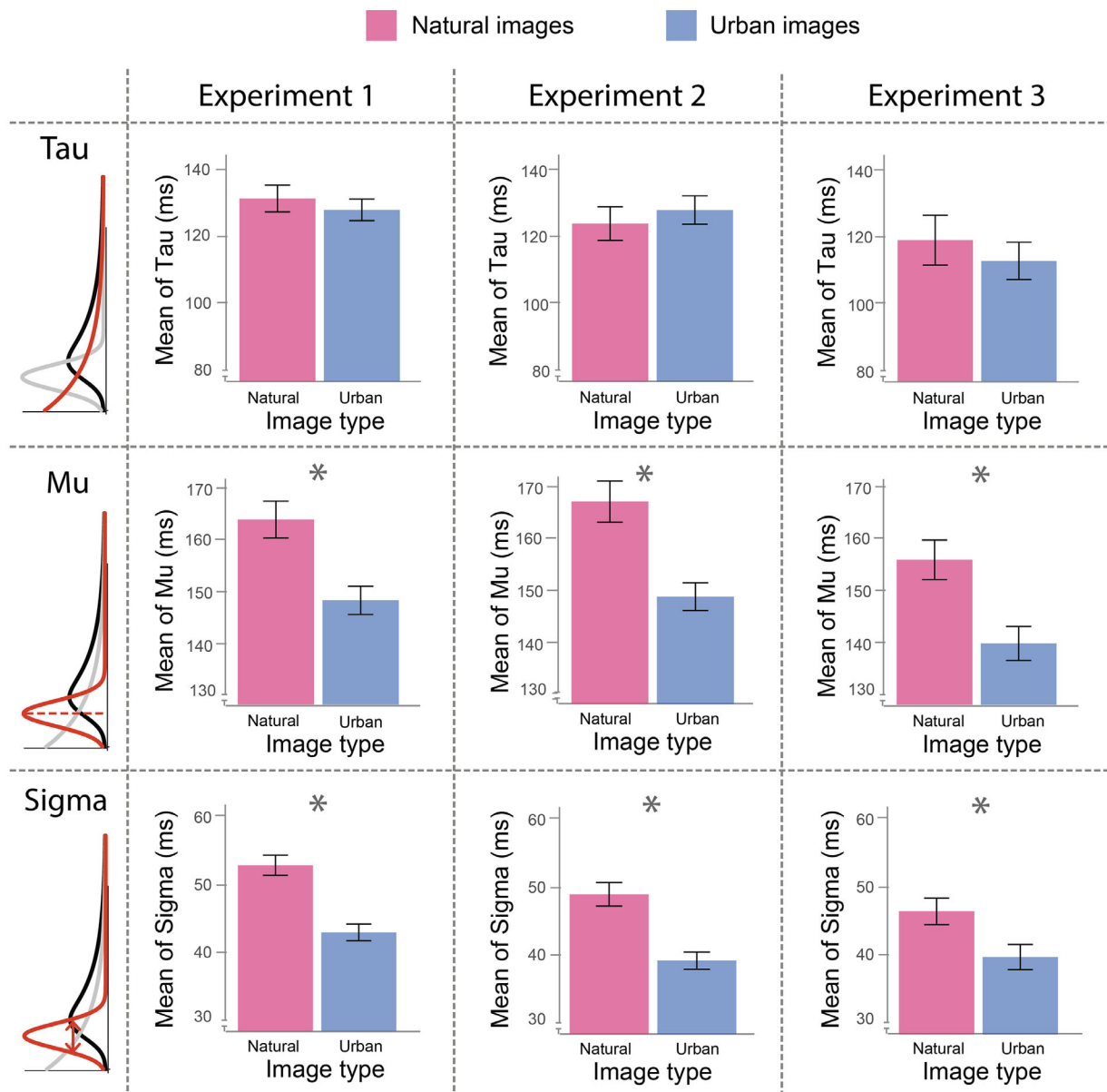


Figure 3. Different types of images dataset: The results of the three experiments are presented in different columns. Estimated parameters of the ex-Gaussian distribution are presented in different rows, with a schematic illustration of the fitted distribution (*black*) and the relevant component (*red*). The results are depicted separately for natural (*pink*) and urban (*blue*) images. * $p < 0.05$. Error bars indicate ± 1 standard error across participants.

displayed in Figure 4, all experiments showed a stable increase across blocks in the τ parameter when viewing the same images, experiment 1: $F(2, 58) = 6.305$, $p = 0.003$, $R^2 = 0.02$; experiment 2: $F(2, 68) = 15.032$, $p < 0.0001$, $R^2 = 0.062$; experiment 3: $F(2, 60) = 5.038$, $p = 0.009$, $R^2 = 0.031$. However, no consistent modulation of the μ parameter, experiment 1: $F(2, 58) = 0.126$, $p = 0.882$, $R^2 = 0.001$; experiment 2: $F(2, 68) = 7.711$, $p = 0.001$, $R^2 = 0.051$; experiment 3: $F(2, 60) = 0.248$, $p = 0.781$, $R^2 = 0.003$, or σ parameter, experiment 1: $F(2, 58) = 0.246$, $p = 0.115$, $R^2 = 0.017$; experiment 2:

$F(2, 68) = 1.698$, $p = 0.191$, $R^2 = 0.018$; experiment 3: $F(2, 60) = 0.395$, $p = 0.675$, $R^2 = 0.005$, was observed. Specifically, whereas in the first and third experiments the μ values increased slightly across blocks, in the second experiment they actually decreased. When observing the novel images, a significant increase in σ values was only found in the second experiment, experiment 2: $F(2, 68) = 6.829$, $p = 0.002$, $R^2 = 0.06$; experiment 3: $F(2, 60) = 0.691$, $p = 0.505$, $R^2 = 0.007$. Importantly, no effect of τ was observed when the images were novel, experiment 2: $F(2, 68) = 0.026$,

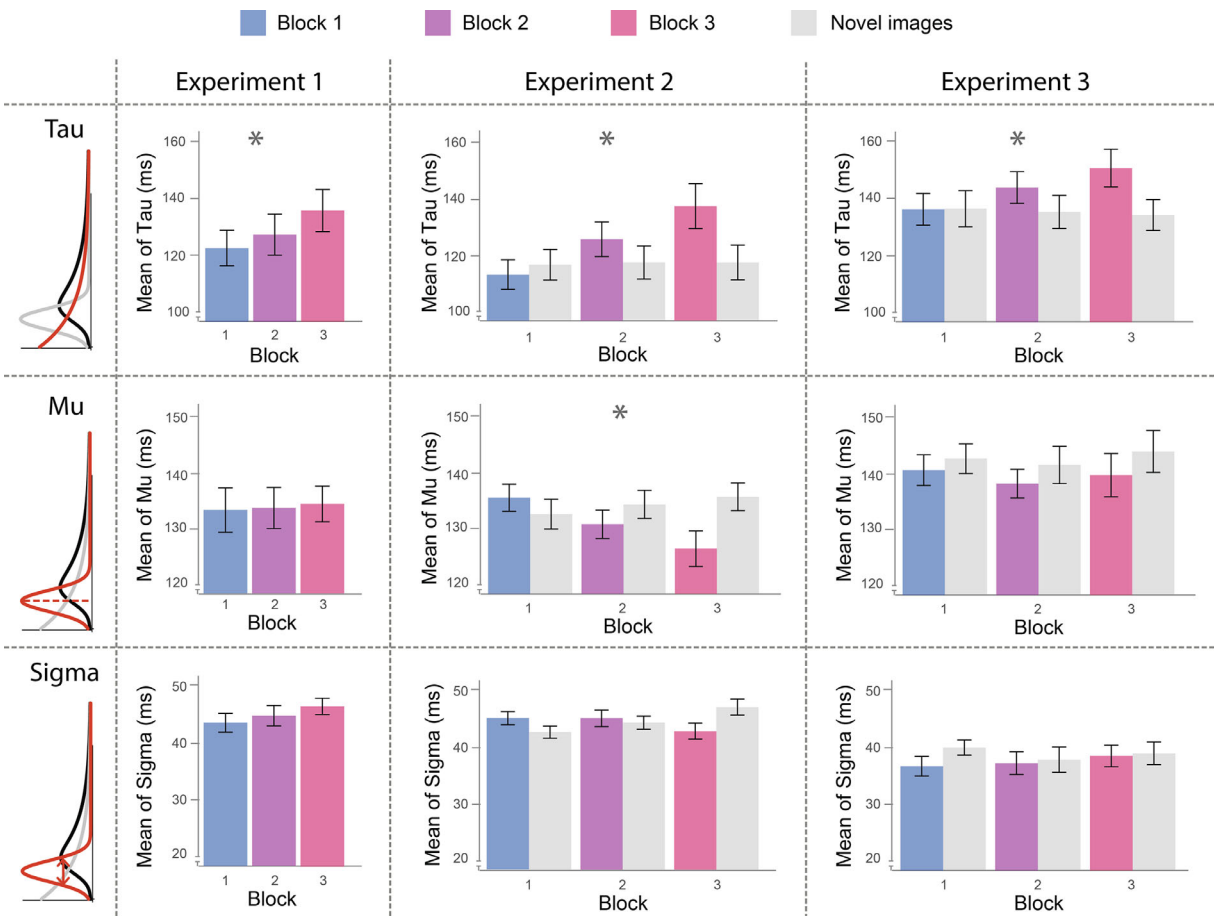


Figure 4. Results of the repetitive displays dataset. Parameters of the ex-Gaussian are presented in different rows, with an illustration of the fitted distribution (*black*) and the relevant component (*red*). The results are depicted separately for the first block (*blue*), second block (*purple*), and third block (*pink*). * $p < 0.05$. Error bars indicate ± 1 standard error.

$p = 0.974$, $R^2 = 0$; experiment 3: $F(2, 60) = 0.211$, $p = 0.81$, $R^2 = 0.001$.

The significant increase in the τ values in all experiments indicates that repetitive exposures to the same images led to an increase in the length of relatively long fixations (i.e., a longer tail), leading to a more prominent exponential component. Interestingly, the impact of repetitive exposures to the same images on the μ parameter was not consistent across blocks. Thus, familiarity with the visual input did not change the duration of all fixations, but rather only a small subset of relatively longer fixations. To shed light on the source of these effects in the empirical distribution, we conducted a quantile analysis.

Quantile analysis

Based on previous studies (Balota & Yap, 2011) we conducted a quantile analysis to compare the mean fixation duration of each decile in the different conditions in each experiment (different types of images

dataset: natural vs. urban; repeated exposures dataset: first block vs. third block) (Figure 5). Higher fixation duration means were observed in natural images almost in all deciles in all experiments (except the highest decile in the second experiment). This pattern of significant differences across all quantiles matches the results of simulations that exclusively changed μ (for a simulation of the ex-Gaussian parameters, see Balota & Yap, 2011). In contrast, the main effect owing to repeated exposures was only observed in the high quantiles. Specifically, the difference between the first and third block was significant from the second quantile in the first experiment, and from the fifth quantile in the second and third experiments. These results resemble the quantile analysis that simulated a change in the value of τ . In particular, in the second experiment an opposite effect was found in the first quantile (i.e., the fixation duration was shorter in the third block than in the first). This finding is consistent with the parametric analysis showing that repeated exposures leads to a decrease in μ in the second experiment, but not in the others. Taken together, the quantile

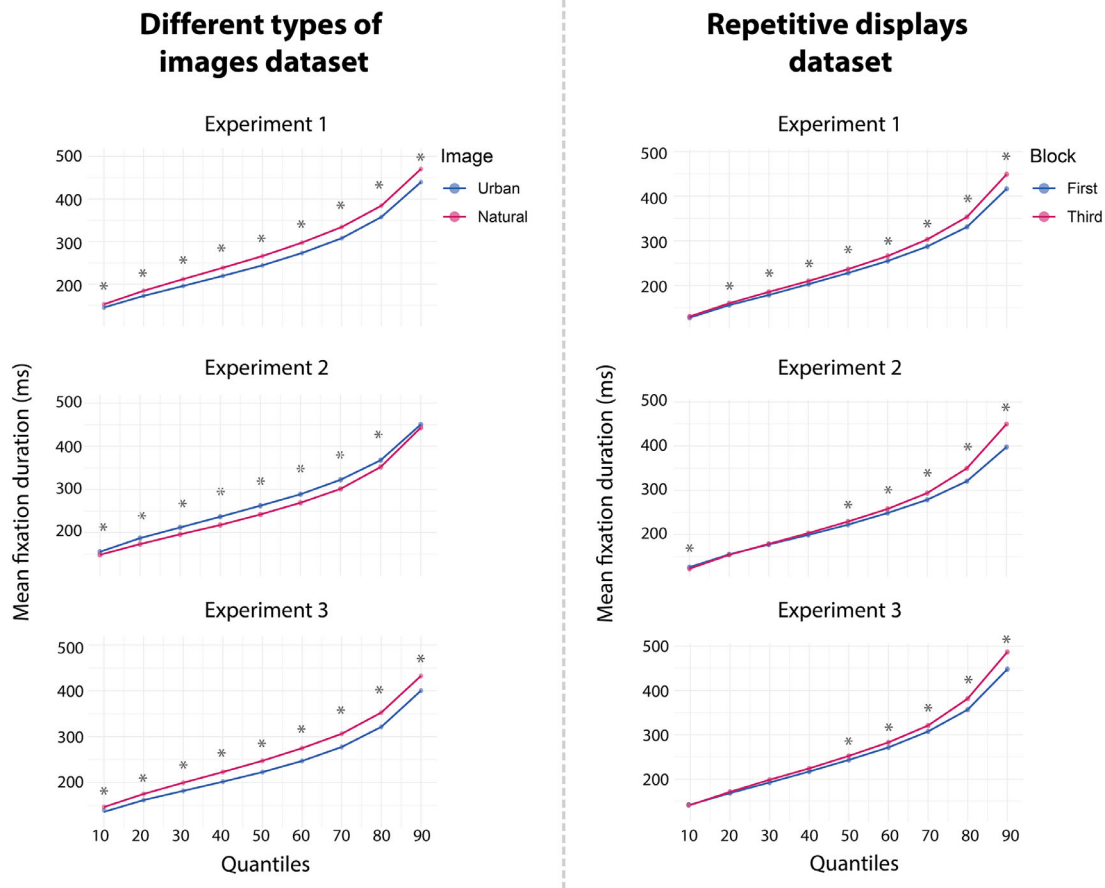


Figure 5. Quantile analysis of the different types of images dataset (*left*) and repetitive displays dataset (*right*). Each dot represents the mean fixation duration (*y* axis) of a certain decile (*x* axis). Significant differences between the two conditions are depicted by asterisks.

analysis demonstrated that a change in the Gaussian component indicates a general modification of all fixations, regardless of their duration. However, when there is a change in the exponential component, it reflects an alteration in some the fixations (i.e., only the relatively long ones). The ex-Gaussian modeling emerged as sensitive to even more fine-grained changes in the empirical distribution; that is, when the durations of the relatively long and short fixations were modified simultaneously, the ex-Gaussian modeling indicated a change in the values of both μ and τ .

Discussion

The mean has become one of the most popular estimators of empirical data for a number of reasons including the fact that it has certain useful properties (e.g., unbiasedness and consistency) and meets important theoretical criteria (e.g., the central limit theorem). However, because it is a single measure that

only captures the center of the distribution, the mean can provide a misleading description of the data. Thus, when the overall structure of the distribution of the data is known, modeling this distribution can provide a more accurate account of the data. Studies on reaction time have used the ex-Gaussian distribution to model the right-tailed distribution of reaction times. These studies have paved the way to modeling other right-tailed empirical distributions, such as fixation durations. Although this approach has been used as a way to estimate fixation duration distributions in reading studies (e.g., [Sheridan & Reingold, 2012](#); [Staub, 2011](#)), it is less frequently used in studies of visual exploration of complex scenes, which still tend to rely on the mean as the main reported measure. Although a handful of studies on scene viewing has already adopted this method (e.g., [Glaholt, Rayner, & Reingold, 2013](#); [Luke et al., 2014](#)), no study has provided a dedicated account of the justifications, the reliability of the ex-Gaussian parameters over time and the possible advantages of this method in revealing differential modulations of fixation duration by divergent experimental factors. In

what follows, we discuss these issues and show that ex-Gaussian modeling has potential benefits for future studies and theories.

Does the ex-Gaussian distribution fit the empirical distribution of fixation durations?

Before modeling a given set of data, it is crucial to examine to what extent the model fits the empirical distribution. Here, we approached this issue in two ways. First, we used the BIC criterion for model selection to demonstrate that the ex-Gaussian model provides a better fit than the Gaussian model, which is often (sometimes implicitly) assumed to be the underlying distribution. Next, we evaluated the fit of the model to each empirical distribution with the Kolmogorov–Smirnov and the empirical likelihood goodness of fit tests and showed that the empirical distributions were not significantly different from the estimated distribution. Taken together, the ex-Gaussian distribution thus emerges as a proper model for the distribution of fixation durations, both in terms of comparison to other models and in its reflection of the empirical data.

After establishing that the ex-Gaussian is a suitable model, we further delved into the ways its parameters vary across participants. Shedding light on variation across individuals is important in demonstrating the usefulness of the model: if all parameters are correlated, they could represent the same underlying phenomenon. In contrast, if the different parameters are not correlated, each parameter could reflect a different underlying mechanism. Across all experiments, we found a strong positive correlation between the two parameters of the Gaussian component: μ and σ . This correlation is not surprising in light of the characteristics of the dependent variable. Because measures of duration are bounded by zero, when the center of the Gaussian is closer to zero (i.e., a low value of μ) the width of the Gaussian should be smaller (i.e., a low value of σ), because negative durations of fixations are not applicable. Accordingly, lower values of μ are accompanied by lower values of σ . In contrast, when μ is larger, the value of σ is less constrained and therefore can be relatively large. Thus, the positive correlation between these two parameters was expected. In contrast, the correlations between the parameters of the Gaussian component (i.e., μ and σ) to the parameter of the exponential parameter (i.e., τ) were low and inconsistent in their sign across experiments. This result suggests that the modeling of the ex-Gaussian distribution may capture two distinctive aspects of the mechanism that generates the durations of fixations.

Finally, we completed the theoretical considerations with an examination of the reliability of the parameters over time. Reliability is a fundamental requirement for all dependent variables because no meaningful insights can be derived from a dependent variable that produces a different result each time it is measured. As far as we know, only one study has addressed the reliability of individual differences in fixation duration distributions (Henderson & Luke, 2014). Their results indicated that, during a scene viewing task, the mean and variance of the fixation duration distributions are reliable over time. Note that the reliability of the mean and variance of the entire ex-Gaussian distribution do not entail the reliability of the ex-Gaussian parameters; rather, both the mean and the variance depend on the Gaussian and the exponential components (mean = $\mu + \tau$; variance = $\sigma^2 + \tau^2$). Therefore, to show that the ex-Gaussian parameters were reliable characteristics of individuals, we examined whether the parameters were correlated over time. As shown in Figure 2, all three parameters were highly reliable over several days, indicating that the reliability was not due to momentary circumstances but persisted. Thus, future scene viewing studies can use ex-Gaussian parameters to reliably describe the fixation duration distribution characteristics of the exploration process.

What benefits can be gained from ex-Gaussian modeling?

The ex-Gaussian distribution is an appropriate model for the distribution of fixation durations. Next, we would argue for the motivation to apply this model. Specifically, we claim that new insights can be gained by using the ex-Gaussian modeling that cannot be derived from the traditional analysis of the mean. Then we discuss possible contributions of ex-Gaussian modeling in light of previous studies and visual exploration models.

To highlight the benefits of ex-Gaussian modeling, we reanalyzed two published datasets from studies reporting changes in the mean fixation duration. In the different types of images dataset, the mean was larger for natural than for urban images, and in the repetitive displays dataset it was larger for images that had already been viewed. Fitting the ex-Gaussian model demonstrated that these effects reflected two different changes in the components of the distribution. In the different types of images dataset, μ and σ were significantly larger when viewing the natural images as compared with the urban ones, but there was no consistent change in the τ values. In contrast, in the repetitive displays dataset, the values of τ increased significantly as the image became more familiar from repeated exposures. In one of the experiments, the effect

on μ was in the opposite direction to the effect of the mean (i.e., μ decreased across repetitive displays and the mean increased). Thus, it can be argued that the effect on the mean in this dataset was likely driven by the change of τ . Moreover, the opposite direction of the effects of τ and μ suggests that these effects may cancel each other out when only inspecting the mean. This finding may imply that some studies could have missed important changes in the distribution by using the mean as the measure of interest.

Taken together, we showed that the observed changes in the mean could be accompanied by two types of modification of the ex-Gaussian parameters: an increase of μ or an increase of τ . To better illustrate the two types of modifications on the empirical distribution of the fixation durations, we compared the deciles of the distributions of each condition. When comparing fixations on the two types of images, the difference between the deciles was consistent throughout the whole distribution; all deciles of the distribution when viewing the natural images were larger than the deciles of the distribution when observing the urban images. In contrast, the difference between the first observation of the images and the third one was detected only in the higher deciles. Thus, consistent with previous studies on simulated data (Balota & Yap, 2011), this analysis showed that the effect of μ stems from a shift of the whole distribution, whereas the effect of τ reflects a change mainly in the tail of the distribution.

Hence, although the manipulations in both datasets changed the mean of the fixation duration, they clearly affected different subsets of fixations. Observing natural scenes led to an increase in the duration of all fixations, whereas familiarity only led to an increase in the duration of relatively long fixations. Therefore, using the mean of the fixation duration masked the source of the effect and could hinder future research. For example, if familiarity causes a change in the duration of the longer fixations, studies on memory-guided gaze should perhaps primarily examine these fixations. Characterizing these fixations (e.g., their location) could shed light on the underlying processes that guide gaze during the inspection of familiar scenes. If longer fixations are deployed toward regions that have been previously scanned, it could be inferred that the lengthening of fixations might be related to recognition and recall processes. In contrast, if these fixations are deployed toward new regions of the scene, this behavior could be attributed to the encoding of new patches of the image. Thus, the ex-Gaussian parameters can provide a more detailed description of the effect, guide future hypotheses, and result in a better understanding of the underlying phenomena.

Studying individual differences is a promising approach in the field of eye movements, as in other fields in cognitive and vision sciences. Previous studies have shown that individuals exhibit reliable differences

in eye movement characteristics acquired in both basic oculomotor tasks, such as prosaccade (Bargary et al., 2017), and in more complex tasks such as reading and scene viewing (e.g., Guy et al., 2019; Henderson & Luke, 2014). A recent study by Luke et al. (2018) exploited the ex-Gaussian modeling to investigate individual differences by exploring the relationship between fixation duration distributions and working memory capacity. The findings revealed that participants with a larger memory span also exhibited lower τ values (a smaller tail) of fixation durations in both reading and scene viewing. This finding is consistent with manual reaction time studies showing a relationship between working memory capacities and τ values (e.g., Shahar et al., 2014). The Luke et al. study (2018) points to two important advantages of using the ex-Gaussian distribution. It allows for a comparison between studies that use different measures that can be modeled with the ex-Gaussian distribution (e.g., reaction times and fixation duration). These comparisons enable a generalization of findings across different fields of research, which may result in a more comprehensive understanding of different cognitive phenomena. In addition, exploring individual differences in the ex-Gaussian parameters and their relationship to other cognitive processes may help to account for the nature of the variance in cognitive abilities between individuals.

Finally, the ex-Gaussian parameters can contribute to process-oriented models of visual exploration in complex scene viewing. Whereas most eye movements studies used the mean to describe fixation duration distributions, models of visual exploration took the distributional nature of fixation duration into account (e.g., Nuthmann et al., 2010; Tatler, Brockmole, & Carpenter, 2017). At least two main attempts have been conducted to model gaze behavior during the inspection of scenes. The first is the LATEST model, which describes the fixation duration as the time until a decision to move the eyes is made (see Tatler et al., 2017). The second is the CRISP model that assumes fixation duration to be determined by two components: 1) a random walk process which determines the timing of the upcoming saccade and 2) a cancellation mechanism which can interrupt and restart the random walk process (for further details, see Nuthmann et al., 2010). These process-oriented models considered the skewedness to the right of the fixation duration distribution, but they did not directly address the ex-Gaussian structure of the distribution. Importantly, the distribution of the output of the models should not be restricted to the ex-Gaussian distribution, because other types of distribution may fit empirical data well. However, the findings derived from using the statistical tool of ex-Gaussian modeling can be harnessed to fine tune process-oriented models. For example, in the CRISP model, the cancellation mechanism leads

to a small number of long fixations. Familiarity with the image also modulates the long tail of the duration distributions, which may hint at a possible link between saccade cancellation and familiarity.

How should the parameters of the ex-Gaussian distribution be interpreted?

There is an ongoing debate in the literature that has modeled empirical data with an ex-Gaussian distribution whether the components of the ex-Gaussian model can be mapped to distinct underlying cognitive processes. Some studies have argued that each parameter of the distribution reflects a different cognitive process. For example, one study (Kieffaber et al., 2006) claimed that the μ component of the manual response time distribution is related to perceptual processes, whereas τ is related to decision processes. By contrast, a later study (Matzke & Wagenmakers, 2009) claimed that this interpretation was specious. By simulating data from the Ratcliff diffusion model (Ratcliff, 1978), they showed that the ex-Gaussian parameters do not correspond with specific parameters of the diffusion model. According to this view, there is a solid evidence that each parameter of the diffusion model is uniquely associated with a distinct psychological processes (Voss, Rothermund, & Voss, 2004; Wagenmakers, Van Der Maas, & Grasman, 2007). Thus, finding that a parameter of the ex-Gaussian model is associated with several parameters of the diffusion model implies that the ex-Gaussian parameters do not reflect a unique cognitive process. For this reason, Matzke and Wagenmakers (2009) called on researchers not to interpret the parameters, but rather to use the ex-Gaussian modeling purely as a descriptive tool.

Between these two approaches, an intermediate solution to the issue of interpreting the parameters of the ex-Gaussian distribution should be considered. This solution takes the view that the components of the ex-Gaussian model do not necessarily reflect a single distinct cognitive process; nevertheless, dissociations between the components can still shed light on cognitive processes by indicating which processes share overlapping mechanisms and which do not. For example, in the reading literature, finding different modulations of the ex-Gaussian parameters in terms of the frequency of a word or its predictability strongly suggests that the mechanisms involved in these two phenomena are somewhat distinct (Staub, 2015).

Although this debate has unfolded in other research domains, such as in the literature on manual response times, it is highly relevant to studies of fixation durations during visual exploration. Because the use of the ex-Gaussian model in visual exploration

remains infrequent the question of how to interpret the parameters remains open. The accumulation of data on different manipulations that affect each component would enable future studies to examine whether the components can be attributed to distinct cognitive processes. Meanwhile, ex-Gaussian modeling is a valuable technique for identifying dissociable mechanism that determine fixation durations.

Conclusion

Although ex-Gaussian modeling has become a common method in studies on manual reaction time and reading, it is rare in studies of visual exploration. Here we demonstrated its advantages in modeling fixation duration during scene viewing, in terms of both theories and models of gaze behavior. Specifically, we showed that a change in the mean fixation duration can be driven by distinct modulations of each ex-Gaussian component. Differentiating between these modulations can shed light on the underlying processes that determine fixation durations. By providing practical guidelines and access to analysis scripts, we hope to encourage future studies to use the ex-Gaussian as a reliable tool to analyze the distribution of fixation durations.

Keywords: scene exploration, ex-Gaussian, eye movements, fixation duration

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Footnotes

¹Code for the analysis is available at https://osf.io/8ckvh/?view_only=2c46aa4ffdbe40c7abd4c16374a01ae3.

²Originally, the experiment was composed of 58 participants, including children, students and the elderly. To ensure that the sample would be age-matched with the other experiments only the student subsample is included here.

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