Drivers' Attentional Instability on a Winding Roadway

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***Abstract*—The spatiotemporal distribution of drivers' attention to preview was inferred from their steering movements while tracking a winding roadway in a laboratory setting. For most subjects, the average driving attentional distribution over six daily sessions was relatively stable and generalized across different control devices. However, there was considerable day-to-day variability in the attentional distributions. This variability was modeled as a strong interaction between two dynamic processes, the attentional emphasis of selected regions and inhibition of surrounding regions. The model combines a novel application of a reaction-diffusion model of biological pattern formation with an optimal control model of attention to preview. The combined model treats attentional dynamics as an example of the biological spacing of a limited cognitive resource, which is also shaped by the demands of action.**

***Index Terms*—Attention, driving, manual control, optimal control, pattern formation, preview, reaction-diffusion, tracking.**

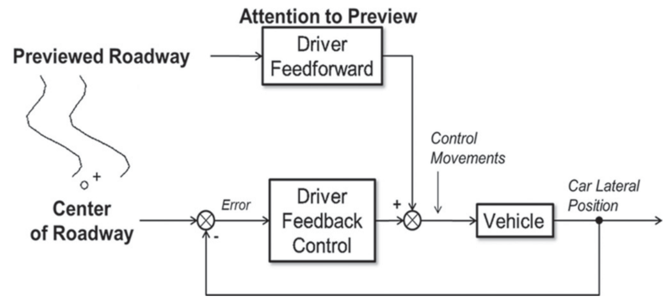

Fig. 1. Roadway display (upper left) and a conceptual model of movement control with preview. Preview extends 1 s into the future at the top of the display. The cross represents the present center of the roadway. Subjects were instructed to keep the circular cursor directly below the cross.

I. Introduction

In tracking, a winding roadway performance is improved by the availability of a preview of the upcoming roadway [1] [2] (see Fig. 1). Jagacinski *et al*. [3] have recently introduced a methodology for measuring the spatiotemporal distribution of attention to preview by analyzing human movements used to track a winding roadway. Building on previous work by Johnson and Phatak [4], Sheridan [5], Levison [6], and others, the previewed roadway was perturbed with a sinusoid of a different frequency at each of ten preview times ranging from 0.1, 0.2, up to 1.0 s. Fourier analysis of the person's tracking movements revealed an amplitude at each of these frequencies. The ratio of this amplitude to the amplitude occurring at that same frequency in a control condition without perturbations provided a signal-to-noise ratio that is interpreted as a measure of attention allocation. It is assumed that the driver has a limited cognitive capacity to process preview and selectively emphasizes or attends to certain preview times depending on the dynamics of the control task. The present methodology measures to what degree various preview times are coupled to the driver's control motions, and does not rely on eye movements to infer attention. The present experimental task used a display that did not require shifting one's gaze. This measurement technique reveals a detailed spatiotemporal distribution of attention, which may be helpful in assessing individual differences in cognitive aspects of driving skill.

The data of Jagacinski *et al.* [3] were obtained from naive subjects over 2 or 3 sessions of approximately 1 h each. The present paper examines this measure of attention with a convenience sample of four subjects who were researchers familiar with the measurement technique, and who tracked for an extended period of 18 sessions in two different laboratory settings. Questions of interest are as follows.

1) Do subjects reach stable asymptotic performance in their distribution of attention to preview?
2) Do subjects exhibit similar patterns of attention in two different laboratory settings, one using a joystick and another using a steering wheel?

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3) Do subjects' exhibit a continuously decreasing pattern of attention for preview times farther into the future as suggested by Miller's optimal control analysis [7], or do they exhibit two discrete points of attention, one close and one far, as suggested by empirical research on car driving and piloting [8]–[11].

II. Method

A. Participants

Four researchers familiar with the measurement technique of Jagacinski *et al*. [3] participated in the study. They ranged in age from 22 to 30 years. Subjects 1 and 3 had participated in the research program for more than 2 years and had significant practice on the experimental task involving the joystick (see below). Subjects 2 and 4 had a slight amount of practice prior to the experiment. All participants passed a test for 20/25 corrected vision. The research was approved by the Institutional Review Board at Ohio State University. Informed consent was obtained from each participant.

B. Apparatus

A winding roadway was tracked in two different laboratories. In Laboratory A, subjects viewed the winding roadway on a 24-in BenQ LED monitor from a distance of 26 in (66 cm). They manipulated a one-dimensional joystick (Measurement Systems 525 constrained to one axis) to keep a circular cursor below a cross that indicated the center of the roadway. Preview of the roadway was provided at 0.05, 0.10, 0.20, 0.30, …,1.00 s into the future and was displayed as two curvy edge lines (see Fig. 1). The horizontal separation of the edge lines decreased by 19% from 0 to 1.00 s of the preview to give an impression of depth. In Laboratory B subjects viewed the winding roadway on a Christie Digital HoloStage Minicave from a distance of 74 in (183 cm). This display provided a low fidelity simulation of driving down a country road at a challenging speed with no additional traffic. The drivers sat in a Playseat and manipulated a steering wheel (Logitech G29 Racing Wheel with no force feedback) to keep the circular cursor below the cross indicating the center of the roadway [see Figs. 1 (left) and 2]. The depiction of the winding roadway was the same as in Laboratory A. The horizontal range of the roadway center was approximately 4.8° of visual angle to the right and left in both laboratories, and both displays were updated at 60 Hz. Both roadway displays could be viewed without shifting one's gaze. The sensitivity of the joystick was 0.27° of visual angle per 1° of joystick movement, which was controlled by finger and wrist movements. The sensitivity of the steering wheel was 0.14° of visual angle per 1° of steering wheel movement, which was controlled with arm movements. Both systems directly controlled the position of the circular cursor.

C. Procedure

Each experimental session consisted of three blocks of four trials. Each trial began with 10 s of warm-up tracking followed by 164 s of data collection. The roadway consisted of the sum of ten sinusoids, six with high amplitudes and four with amplitudes that were one-fifth larger. The six high amplitude sinewaves determined the input bandwidth, which was approximately 3 rad/s. One block had additional sinusoidal observation-noise disturbances added to the display of the roadway, one block had sinusoidal wind gust disturbances of the cursor, and one block had no added disturbances. A full counterbalance of the ordering of the blocks was used across each set of six sessions. The initial phases of the sinusoids varied from trial to trial. There were three sets of six sessions for a total of 18 sessions. Subjects 1 and 2 had 12 sessions with the steering wheel followed by six sessions with the joystick. Subjects 3 and 4 had 12 sessions with the joystick followed by six sessions with the steering wheel. There was a one-to-five-week break between the second and third sets. After each block subjects received feedback on their median root-mean-squared error over the four trials.

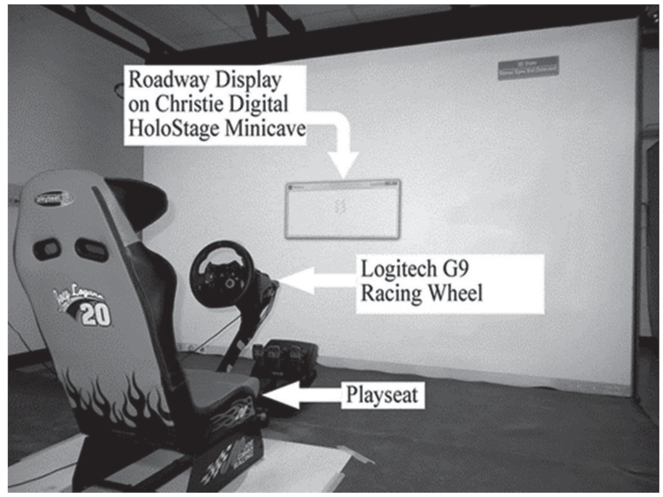

Fig. 2. Laboratory B with a steering wheel controller.

D. Measure of Attention to Preview

In the block with additional sinusoidal observation noise, ten different sinusoids with distinct frequencies perturbed the road at ten preview times ranging from 0.1 to 1.0 s into the future. Fourier analysis of the joystick or steering wheel movements determined the median amplitude at each of these ten frequencies. The ratio of this amplitude to the median amplitude at that same frequency when there was no additional observation noise provided a signal-to-noise ratio that was interpreted as a measure of attention to each of the ten previewed roadway positions. The observation noise frequencies interleaved the frequencies of the roadway and were arranged so that the fastest perturbation frequency was at the 0.1 s preview time, and the slowest was at the 1.0 s preview time. Previous research revealed that this ordering resulted in higher signal-to-noise ratios than the reverse ordering [3].

E. Measure of Error Nulling

Wind gust disturbances consisting of ten frequencies different from the roadway frequencies were added to the cursor position

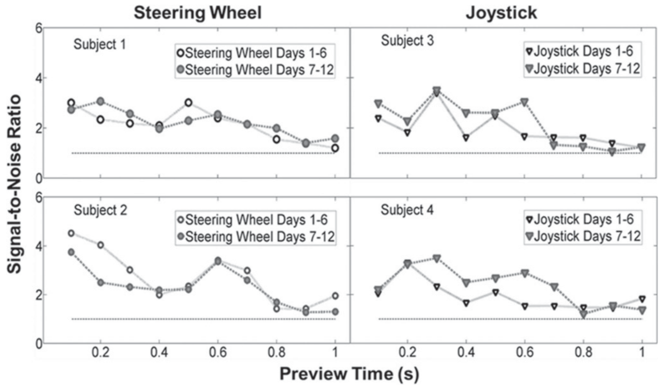

Fig. 3. Attentional signal-to-noise ratios for Days 1–6 and Days 7–12. Circles represent the steering wheel, and inverted triangles represent the joystick (pivoting about a fixed axis). The unfilled symbols are for Days 1–6, and the gray symbols are for Days 7–12. Subjects used the same control device for Days 1–12.

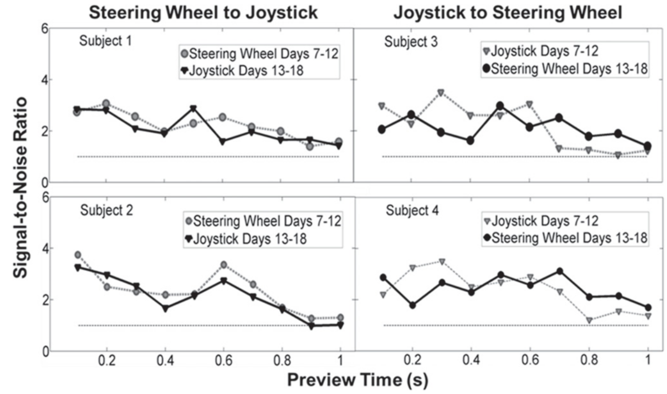

Fig. 4. Attentional signal-to-noise ratios for Days 7–12 and Days 13–18. Circles represent the steering wheel, and inverted triangles represent the joystick. The gray symbols are for Days 7–12, and the black symbols are for Days 13–18 when the subjects switched to a different control device.

for one of the three blocks of trials. Because these disturbances were not previewed, the response of the subject at these frequencies provided a measure of error nulling independent of the response to preview. Fourier analyses were conducted to determine the median amplitude ratio and phase shift from error to system output (commanded cursor position). A simplified McRuer crossover model was fit to these data [12]. This model posits that the describing function for the person plus the control system can be approximated as a gain, an integrator, and a time delay in a feedback loop. The log–log plot of output to error amplitude ratio versus frequency for this model is linear and has a slope of –1 due to the integrator. The frequency in rad/s at which the amplitude ratio is equal to 1 is numerically equal to the gain *K*. A plot of phase shift versus frequency is also linear and has an intercept of –90° due to the integrator in the crossover model. The slope of the linear trend, rad versus rad/s, is equal to the time delay. The median amplitude ratio and phase shift were calculated across the four trials in a block at each measurement frequency. The medians at the middle six frequencies out of ten were used to estimate the gain and time delay for a block of trials.

III. Results

A. Attention Distribution

A comparison of the attention signal-to-noise ratios at the ten measured preview times for Days 1–6 and Days 7–12 is shown in Fig. 3. All subjects exhibited significant effects of the preview time ($p < .01$) and generally exhibited stable patterns across the two sets of six days. Only Subject 4 showed a statistically significant practice effect ($F(1,10) = 4.95$, $p = .05$) corresponding to higher signal-to-noise ratios on Days 7–12.

A comparison of the attention signal-to-noise ratios for Days 7–12 and Days 8–13 is shown in Fig. 4. All subjects exhibited significant effects of the preview time ($p < .01$). Only Subject 3 exhibited a significant effect of joystick versus steering wheel, an interaction ($F(9,90) = 2.18$, $p < .05$) reflecting a greater emphasis of longer preview times with the steering wheel. The

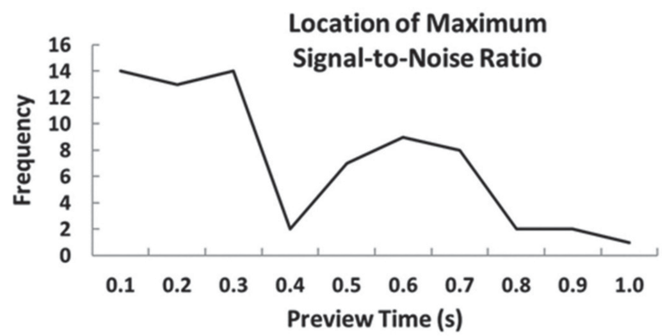

Fig. 5. Preview times at which the *maximum* signal-to-noise ratio occurred across all subjects and days (4 subjects $\times$ 18 days $=$ 72 signal-to-noise attentional distributions).

other three subjects showed relatively stable patterns of attention across the joystick and steering wheel.

Despite the relative stability of the six-day average attentional patterns, there was striking variability in the day-to-day measures of attention. Fig. 5 shows the preview times corresponding to the highest daily signal-to-noise ratio across all 18 days and four subjects. There are two groups of preview times with similarly high frequencies. Preview times 0.1, 0.2, and 0.3 s had the maximum signal-to-noise ratio on more than half of the sessions (57%), and preview times 0.5, 0.6, and 0.7 s had the maximum signal-to-noise ratio on one-third of the sessions (33%).

Plots of the signal-to-noise ratios for Days 8–11 are shown in Figs. 6 and 7 for the two subjects with the lowest error scores on Days 7–12. Subject 2 showed a strong peak at 0.6 s on Days 8 and 11; on Days 9 and 10 there was a strong peak at 0.1 s. Subject 4 showed strong peaks at 0.5 and 0.6 s on Days 8 and 9; peaks at times 0.1, 0.2, or 0.3 s occurred for all four days. These patterns of instability across days and the two regions of maximal signal-to-noise ratio in Fig. 5 suggest that the peaks in the 0.1–0.3 s range and the 0.5–0.7 s range are distinct foci of attention. They may alternate across days as illustrated in Fig. 6, or they may co-occur as illustrated in Fig. 7.

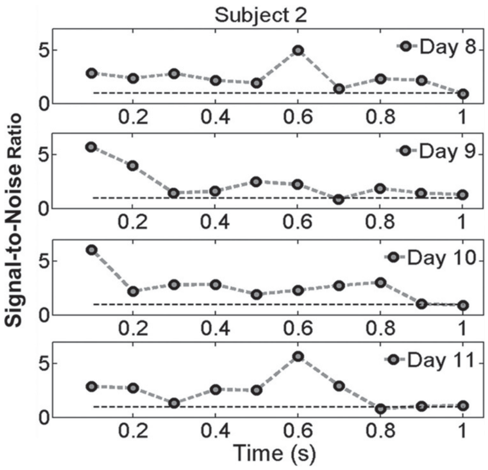

Fig. 6. Attentional signal-to-noise ratios for Days 8–11 for Subject 2 using a steering wheel.

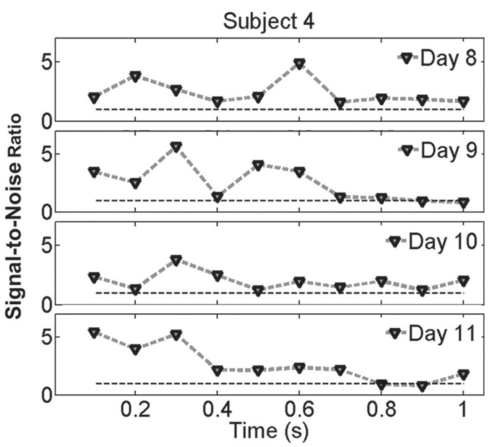

Fig. 7. Attentional signal-to-noise ratios for Days 8–11 for Subject 4 using a joystick.

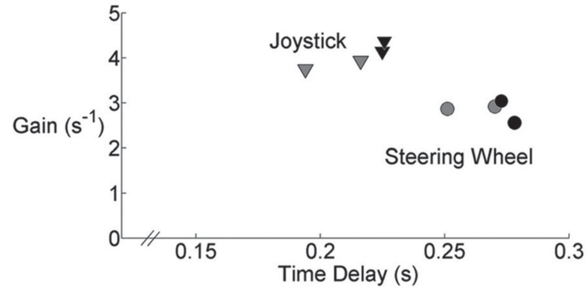

Fig. 8. Error nulling gains (K) and time delays estimated from the crossover model. Each symbol represents a single subject. Gray symbols are for Days 7–12. Black symbols are for Days 13–18.

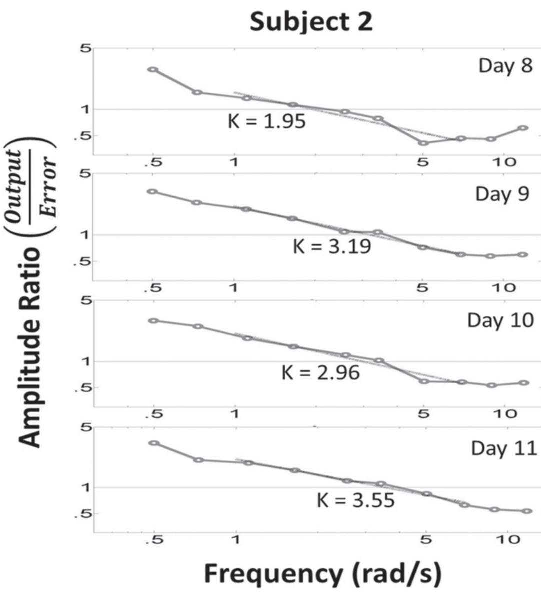

Fig. 9. Amplitude ratios for the relationship between system output (commanded cursor position) and error for Days 8–11 for Subject 2 using a steering wheel.

Another possibility is that these peaks are a result of measurement noise. However, similar experiments [13] in which only part of the preview was visible provided an estimate of measurement noise at preview positions that were not visible to the subject. Signal-to-noise ratios of magnitude 3 or greater spuriously occurred less than 1% of the time at these hidden preview positions for the data in single daily sessions. These experiments used a rate control, which has exhibited similar signal-to-noise patterns as a position control system. Given the large magnitudes of the signal-to-noise peaks in the daily sessions in Figs. 6 and 7, it is highly unlikely that they reflect measurement noise.

B. Error Nulling

An analysis of error nulling on Days 7–12 and Days 13–18 using the McRuer Crossover Model revealed systematic differences in feedback control between the joystick and steering wheel for each subject ($p < .01$). The crossover frequency at which the amplitude ratio equals 1.0 was estimated from a linear fit to the middle six measurement frequencies plotted logarithmically against log amplitude ratio.

The crossover frequency is numerically equal to the gain K in the McRuer Crossover Model. The time delay was estimated from the slope of a linear fit to phase lag plotted against the middle six measurement frequencies. The joystick controller resulted in higher gains K and lower time delays than the steering wheel (see Fig. 8). These differences can be attributed to biomechanical differences between the limbs (fingers and wrist for the joystick versus arms for the steering wheel) and hardware (light joystick handle versus more massive steering wheel). Similar differences in effective time delay are reported in [14]. The pattern of feedback control performance was highly stable across days, in contrast to the attentional signal-to-noise ratios. This stability is exemplified in the decreasing pattern of amplitude ratios for Subject 2 in Fig. 9.

Given the 3 rad/s input bandwidth, one would expect the crossover model gain to be 3 or higher [12]. The gain K is numerically equal to the frequency in rad/s at which the output to error amplitude ratio "crosses over" from above 1.0 to less than 1.0. With the steering wheel subjects exhibited gains near 3. With the joystick their gains were around 4 (see Fig. 8).

IV. Modeling Attentional Pattern Formation

A dynamic model of selective attentional emphasis and inhibition of surrounding regions is proposed to interpret the patterns of spacing and day-to-day instability in the attentional signal-to-noise ratios (see Figs. 5–7). Broadly speaking, the function of attention is to emphasize particular aspects of a creature's informational environment that are relevant to achieving present goals and/or the need to switch goals. Selective emphasis is needed because of a creature's limited cognitive and action capabilities in information-rich environments. Sustained stable attention to fixed spatiotemporal loci may be necessary for particular tasks like tracking a moving target. However, if attention was very stable, it might limit responses to new stimuli that indicate a need to interrupt the present task and switch goals to address some imminent danger or opportunity. It would therefore not be surprising if attention had a level of stability that could be easily interrupted by environmental perturbations.

Previous efforts to model aspects of attentional dynamics include the metaphor of a spotlight which can be quickly moved to different locations [15], [16], a spotlight or zoom lens with adjustable width [17], [18], and internal oscillators which can become entrained with external rhythmic patterns as in musical contexts [19]. The present modeling effort posits two component processes, selective attentional emphasis (A) and inhibition of surrounding regions (I) that have been widely discussed by attentional researchers (see [20] for a review). This model describes the shapes of average attentional distributions over the spatiotemporal display of the preview as well as variability over successive blocks of trials. Leber [21] noted strong trial-to-trial variations in the degree to which attention could be captured by irrelevant stimuli, and also noted correlated changes in brain activity in the middle frontal gyrus. The present model emphasizes attentional instability as a key aspect of behavior and tries to exploit the detailed spatiotemporal structure revealed by the present measurement technique to understand attentional dynamics.

The present model of attention is an adaptation of a type of biological model of dynamic pattern formation that has been used to model the development of embryos [22] and cortical feature maps [23], the rhythmic spacing of color striations on seashells [24], and similarly many other examples of biological pattern formation (see [25] for a review). This type of model was introduced by Turing [26] to describe the emergence of features in embryos (morphogenesis) from relatively uniform initial conditions. It is called a reaction-diffusion model and consists of two processes, an activator and an inhibitor (e.g., [24, p. 23], Table I) whose dynamics are described by a system of two partial differential equations

$$\begin{aligned}\partial A/\partial t &= \left(e^{-M(x-0.1)/0.9}\right)\left(sA^2/I + sb_A\right) - r_A A \\ &\quad + D_A \partial^2 A/\partial x^2 \\ \partial I/\partial t &= \left(e^{-M(x-0.1)/0.9}\right)\left(sA^2 + b_I\right) - r_I I \\ &\quad + D_I\, \partial^2 I/\partial x^2 \end{aligned} \tag{1}$$

TABLE I
GMM Model

Symbol	Quantity	Values
A	Attentional emphasis	$0 \le A \le 5$ initial conditions = 1.5
I	Inhibition of surrounding regions	$1 \le I$ initial conditions = 1.5
x	Spatial display of preview actively attended	$0.1 \le x \le 1.0$ in Fig. 10 $0.1 \le x \le 0.9$ in Fig. 11 $0.1 \le x \le 0.9$ in Fig. 12
s	Production rate amplifier	0.15[1 + 0.03norm. distrib. (0,1)]
b_A	Production rate constant for A	0.01
b_I	Production rate constant for I	0.00
r_A	Decay rate for A	0.03
r_I	Decay rate for I	0.06
D_A	Diffusion coefficient for A	0.0011 in Fig. 10 0.01 in Fig. 11 0.01 in Fig. 12
D_I	Diffusion coefficient for I	0.0440 in Fig. 10 0.40 in Fig. 11 0.40 in Fig. 12
M	Exponential shaping of production rate	0.00 in Fig. 10 0.45 in Fig. 11 0.90 in Fig. 12

The activator (A) has positive feedback such that it grows in strength over time once started by a sufficiently large perturbation in growth rate or initial condition. The activation slowly spreads through space or diffuses at a rate determined by D_A. The activator also creates an inhibitor (I) at that location that limits its growth. The inhibitor spreads much more quickly through space to limit the growth of other nearby activators $(D_I > D_A)$. The activator and inhibitor dynamics also include decay rates, r_A and r_I, that limit their growth and constants s, b_A, and b_I that adjust the production rates (see Table I). This model has qualitative characteristics of emphasizing certain regions in a patterned manner and of stochastic variability. These are qualitative characteristics of human attention, so we wanted to test whether this common dynamic found in various species could also describe aspects of human attention.

For modeling attention, the activator process (A) will be attentional emphasis, and the inhibitor process (I) will be inhibition of attention to immediately surrounding regions. The general intent is to consider the spatial distribution of attention as an instance of a general class of biological pattern formation processes. This model has a rhythmic spacing of areas of attentional emphasis that is directly related to the magnitude of the diffusion coefficients, D_A and D_I [27]. In Fig. 10 the diffusion coefficients are relatively small (see Table I), and multiple peaks of attentional emphasis are tightly spaced. The model

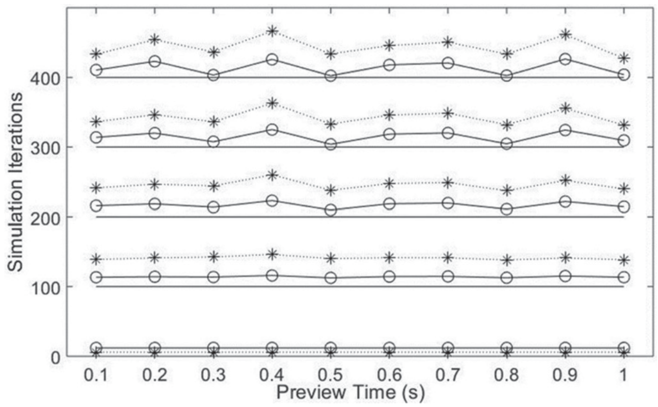

Fig. 10. Rhythmic spacing of the attentional emphasis evolving from uniform initial conditions and random perturbations of growth rate, *s* in (1). Circles represent attentional emphasis (*A*), and ∗'s represent inhibition (*I*/2). Small values of the diffusion coefficients, D_A and D_I, produce tight spacing of the regions of the attentional emphasis after 400 temporal iterations. See Table I for parameter values.

was simulated with ten discrete values for *x*, which correspond to the positions of the various preview times in the display in Fig. 1.

To extend this model to the tracking task, an additional decreasing exponential function multiplies the attentional emphasis (*A*) and inhibitor (*I*) production rates (1). The constants 0.1 and 0.9 scale the exponential multiplier to equal 1.0 when $x = 0.1$ and e^{-M} when $x = 1.0$. This term reflects the optimal control solution for tracking with finite preview developed by Miller [7]. Namely, Miller showed that the optimal attentional distribution to preview is a decreasing exponential for a velocity control system. The present experiment used a position control. If a position control is approximated as a lag with a high bandwidth, Miller's method gives the corresponding optimal attentional weighting of the preview as an exponential function that rapidly decreases with increasing preview times. To reflect this task demand to emphasize shorter preview times, both the attentional emphasis and inhibitor production rates are multiplied by a decreasing exponential. This function will therefore favor the growth of attentional emphasis at short preview times. A similar positional gradient was used by Gierer and Meihnardt [22] in models of embryo development. The equations for the combined model will be referred to as the Gierer–Meinhardt–Miller Model or GMM model.

A second way of controlling the inherent rhythmicity of spatial attention is to limit the range of attention. The locus of spatial attention has been previously described as having an adjustable range or width [15], [17], [18]. The spatial rhythmicity of the reaction-diffusion dynamics is more evident when the spatial range of attention is larger. Therefore, a control strategy for limiting this rhythmicity in the present task and emphasizing short preview times would be to limit the range of attention to less than the full range of ten positions (preview times) shown in Fig. 1. In the present modeling effort (see Figs. 11 and 12), the active range of attention was limited to nine positions to better approximate the subjects' data.

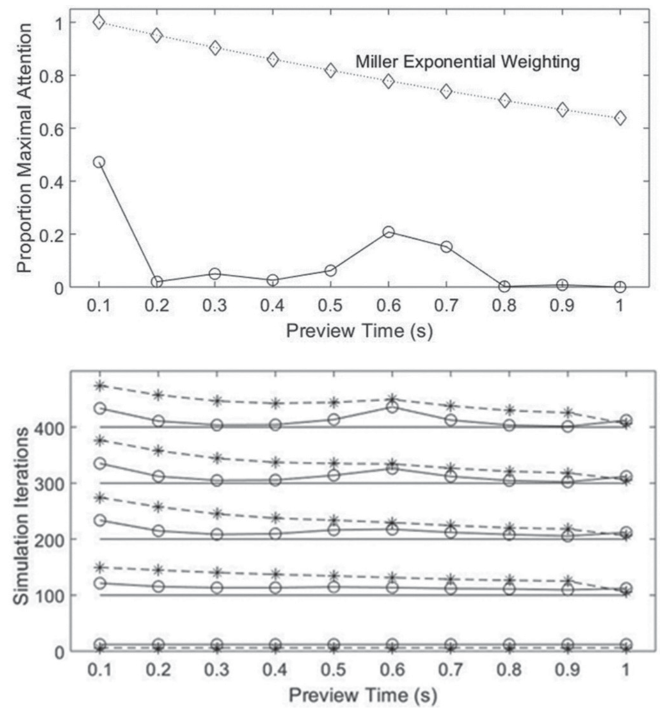

Fig. 11. (Bottom) Evolution of an attentional distribution to preview with a *weak* exponential decrease ($M = 0.45$) in the GMM model. Circles represent attentional emphasis (*A*), and ∗'s represent inhibition (*I*/2). (Top) Frequency distribution of the location of the *maximal* attention (*A*) over 500 simulations of the model with 400 temporal iterations each.

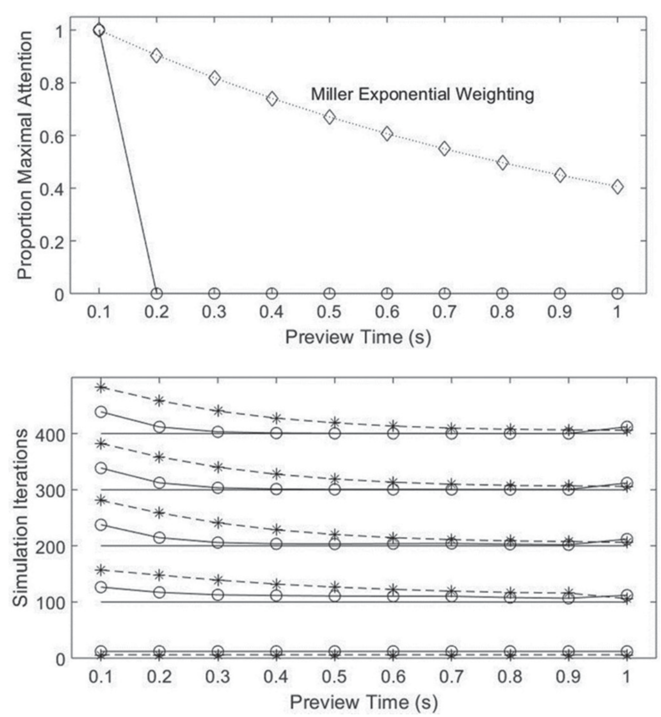

Fig. 12. (Bottom) Evolution of an attentional distribution to preview with a *strong* exponential decrease ($M = 0.90$) in the GMM Model. Circles represent attentional emphasis (*A*), and ∗'s represent inhibition (*I*/2). (Top) Frequency distribution of the location of the *maximal* attention (*A*) over 500 simulations of the model with 400 temporal iterations each.

Figs. 11 and 12 show the development of attentional distributions from uniform initial conditions of *A* and *I*. The model simulation begins with a random set of perturbations of the attentional emphasis and inhibition production rates, *s* in (1), at each of nine preview times (positions on the tracking display in Fig. 1). As some of these attentional foci start to grow, they simultaneously send out rapidly diffusing inhibition that limits the attentional growth at other positions. As these spatially distributed processes interact over time they can produce patterns of primary emphasis at short preview times (see Fig. 12) or primary emphasis at short and/or intermediate preview times (see Fig. 11) depending on the exponent of the Miller function. Fig. 11 (top) mimics the two-clump pattern in Fig. 5, although the clump at the shortest preview time does not show the variability exhibited by the subjects. This attentional pattern formation is presumed to occur early in a trial and then continue throughout the remainder of the trial.

This model attributes the daily instability in attentional focus in Figs. 5–7 to the reaction-diffusion dynamics and the form of the Miller shaping function. The interaction of the attentional emphasis and inhibition of surrounding regions has a level of stability that is sensitive to small random variations in the production rates. The Miller exponential shaping is a way of trying to control these sensitive processes to emphasize short preview times. The Miller function is a smooth exponential; however, because it acts on complex reaction-diffusion dynamics, the resulting attentional distributions (see Fig. 11) may not be smoothly decreasing, but instead form clumps of emphasis. The clumps are due to the reaction-diffusion dynamics, which is a model of biological spacing. In the case of Meinhardt's seashells [24], the spacing dynamics lead to highly differentiated patterns of coloration. In the case of attention, the advantage of spacing may be to limit focusing too much of a limited cognitive resource in a single delimited region.

V. Discussion

A. Detailed Measure of Attention

This longitudinal study revealed that the feedforward attentional pattern of signal-to-noise ratios was generally stable when averaged across multiple six-day periods and transferred across physically different control devices and limb movements for most subjects (see Figs. 3 and 4). In contrast, feedback parameters of error nulling (gain and time delay) were strongly influenced by the control devices and limbs (see Fig. 8). This pattern of selective influence supports the common modeling assumption that feedforward control and feedback control are distinct behavioral processes [1], [2]. Converging evidence is that this same measurement technique found roadway bandwidth to selectively influence feedback control and not feedforward control [3]. With much more complex dynamic systems, feedforward also exhibits longer learning times [28]. Therefore, feedback and feedforward are behaviorally distinct processes.

In contrast to the stability of six-day average attentional signal-to-noise distributions, day-to-day variability was quite marked. One interpretation of these data is that the peaks that occurred at 0.1–0.3 s and at 0.5–0.7 s of the preview (see Figs. 5–7) are a form of attentional spacing that results from the influences of two complementary, but somewhat unstable processes. A dynamic theory of the attentional emphasis and inhibition of surrounding regions was proposed as underlying processes to account for this pattern of instability. The instability of the feedforward attentional dynamics contrasts sharply with the relatively stable pattern of feedback movement dynamics (see Fig. 9) that were approximated as a simple lag with an internal time delay, i.e., the crossover model [12].

One objection to this interpretation might be that some researchers have proposed two separate loci of attention to preview for car driving (e.g., [8]–[10]; for helicopter control, see [11]). For example, the steering dynamics of a car can be approximated as an acceleration control system. Feedback control requires lead compensation, which can be implemented by using yaw error to extrapolate current lateral position error [29]. The perception of these angular and lateral errors would occur close to the present car position. In contrast, Land and Horwood [8] estimated that the perception of curvature for feedforward control is at about 0.8 s of preview. Miller [7] used optimal control theory to predict heightened feedforward attention in the region of 0.7 s of preview depending on the relative emphasis of error versus effort with an acceleration control system. Land and Lee [30] and Macadam [31] have estimated that preview even greater than 1 s is useful in car driving. Therefore, the information requirements for feedforward and feedback control would *primarily* create the need to attend to two distinct regions of preview, one close and one far. This interpretation would not preclude a behavioral role for the presently proposed attentional dynamics to influence the relative positions of the two attentional regions and their relative stability.

In contrast to typical car dynamics, the present experiment used a position control system. If one approximates a position control as a lag with a high bandwidth, one can use Miller's method [7] to determine the optimal attentional weighting for feedforward control with a position control system. The distribution has a high attention weighting at short preview times and exponentially decreases at a rapid rate with increasing preview time. In this case, one would expect feedback and feedforward control to rely on information close to the vehicle. Converging empirical evidence is provided by Ito and Ito [32]. They found that tracking error decreased with up to about 0.25 s of the preview for a position control, and that longer preview was beneficial for higher order dynamics. The two separated regions of attention found in the present experiment might therefore arise *primarily* from the proposed attentional dynamics rather than from the information requirements of the task, which are different from typical car dynamics.

Another objection to the present modeling might be that the peaks in the 0.5–0.7 s range are a result of measurement noise. As noted above, estimates of measurement noise from previous studies indicate that a signal-to-noise ratio greater than 3 occurs less than 1% of the time [13]. Second, the range of the peaks, 0.5–0.7 s, is rather delimited. 0.4 s is rare, and 0.8–1.0 s is rare (see Fig. 5). This limited range is consistent with the proposed model of attentional dynamics. Namely, the balance between the two separate processes, A and I, leads to a relatively consistent spacing.

A fundamental structural aspect of attention is whether it is unitary or whether it can be allocated to separate spatial locations [33]. For the present model, the answer is "both." Namely, the dynamic structure of attention leads to the emphasis of separate spatial regions. However, there are continuous fields of both attentional emphasis and inhibition that span the range of attention (see Fig. 11). The spacing of the attentional regions of emphasis is not arbitrary; rather, it is constrained by the underlying dynamics. Research on eye movements has found that in walking, driving, and other tasks people tend to direct their gaze toward where they will be acting 0.5 to 1 s into the future to strengthen anticipatory responding (see [34] for a review). The present model suggests that attention can be directed at such a spatiotemporal region and simultaneously at a closer region by controlling attentional dynamics.

B. Optimal Control Considerations

Subjects in the present experiment emphasized preview positions from 0.1 to 0.7 s (see Figs. 3 and 4) rather than only the short preview times as would be expected from Miller's [7] optimal control model. There are at least three possible interpretations of this difference.

First, Miller's optimal control modeling demonstrates that the relative emphasis on minimizing mean-squared error and mean-squared effort (control stick movement) should influence the shape of the attentional distribution. The exponential function emphasizing short preview times should decrease more quickly with an emphasis on error minimization and more slowly with an emphasis on effort minimization. If these experienced subjects were emphasizing error minimization, then their attentional distributions would be expected to be short and steep. The wide range of the experienced subjects' attentional distributions suggests that they were minimizing movement effort. However, this conclusion seems unlikely given that their effort scores (root-mean-squared control stick movement) closely matched the root-mean-squared pathway excursion.

A second possible interpretation is that using the Miller exponential function to emphasize short preview times may be attentionally effortful [35]. These experienced subjects may have been trying to lessen attentional effort, which allowed the reaction-diffusion dynamics to have more influence in forming clumps of attentional emphasis. Kahneman [35] has argued that attention to multiple sources of information can occur in parallel when the overall level of attention is low. In contrast, at high levels of effort, attention is likely to be concentrated on a single source of information. The peak signal-to-noise ratios produced by these experienced subjects are high (see Figs. 6 and 7), which suggests the subjects were not minimizing attentional effort.

A third possible interpretation is that the observation noise added to the display of the path to measure the signal-to-noise distributions created greater uncertainty in the previewed path position. These experienced subjects may have used a wide range of attentional emphasis in order to obtain a more reliable estimate of path position by combining information from multiple positions. This wide range of attention then allowed the reaction-diffusion dynamics to create clumps of attentional emphasis that would not occur with a more restricted range of attention. The simulation in Fig. 11 used a range of attention from 0.1 to 0.9 s, which was sufficient to demonstrate the secondary clump of attention around 0.6 s of preview. If the range of attention is restricted to 0.5 s in the simulation, there is no secondary clump of emphasis. The range of attention may be an important behavioral variable in allowing the spatiotemporal rhythmic nature of attention to be evident.

C. Conclusions and Future Directions

In summary, from an abstract perspective, the spatiotemporal distribution of attention may be considered an example of spacing dynamics similar to those that have been investigated by biologists in contexts ranging from the striation of seashells to the formation of branch structures [25]. This pattern formation is a type of complex spatial rhythm. In the present context, the implication is that attentional dynamics are inherently rhythmical, a point that has been previously raised by Jones and colleagues in their studies of attention to sound patterns [19], [36], [37] and in more physiological theorizing [38], [39]. Two types of control strategies for dealing with attention's inherent rhythmicity in the present task are spatial biasing of the growth processes for attention and inhibition (Miller exponential) and limiting the range of attention. The details of how these attentional control strategies may interact with movement control in other contexts is a topic for future research.

This new technique for examining attention to preview should be explored with higher order dynamics more representative of automotive control. The present method does not rely on eye movements, but instead measures which aspects of the preview are coupled to the driver's control movements. Eye movements are correlated with attention and can indicate brief changes in attentional focus. However, as noted by Land [40] it is often not clear what aspects of the visual field are being emphasized for a given gaze direction. The present methodology can be used in conjunction with eye movements to provide additional detail regarding drivers' attention. Future research should also develop techniques to shorten the present 3-min measurement period and reduce the amount of observation noise needed to assess the attentional distributions.

The present study used nonnaive subjects and measured their performance over an extended period of time. These conditions maximize the likelihood of stationary performance and strengthen the argument that observed variations in the attention distribution reflect an inherent instability. Future research can proceed to examine how individual differences in driving skill [41], [42] are related to attentional distributions in various populations with the goal of improving driver safety.

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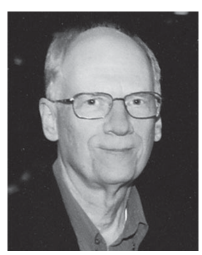

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