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Modelling attention levels using microsaccade rates in response to vibrations in the peripheral field of vision

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Abstract

Viewer's eye movements and behavioural responses were analysed in order to determine the relationship between selective perception and visual attention during a dual detection task in the central and peripheral fields of vision. A hierarchical Bayesian modelling technique was introduced to extract local directions of attention paying behaviour chronologically in order to design better functioning information displays. The model was constructed based on the response accuracy of stimulus detection and temporal changes of the microsaccade rate. In the results, the dominance of the response in the peripheral field of vision is confirmed to be deviations in the estimated parameters. Also, chronological changes in levels of attention and the contribution of these changes to behavioural responses were examined. The relationship between behavioural responses, microsaccade rate, and the directional dominance of certain viewing areas in the peripheral field of vision were discussed, in order to evaluate the level of visual attention of viewers.

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1. Introduction

Discussion of the human vision system often concerns the two types of vision; the central and peripheral fields of vision. The visual characteristics of each are different and function independently [1, 2]. Most studies of visual perception and eye tracking focus on visual interests in the central region of the field of vision [3]. In particular, perception of motion in the peripheral field of vision has been often discussed [4], and the contributions of the peripheral field of vision are emphasised in visual search tasks [5]. Visual display systems and presentations have been used to study the functions of the peripheral field of vision [6–8], and some degree of influence of eye movements has been reported [9]. The independent function of the peripheral field of vision was employed to obtain additional information from visual display equipment using a head mounted display (HMD) [10, 11]. In the visual presentation, visual activity in the peripheral field of vision is examined by measuring the performance detection of vibration targets [12, 13]. If detection performance depends on the region of peripheral direction, either or both the locality of the level of attention being paid or the level of viewing ability may be influenced. It means that locality or level of viewing ability or both may be influenced. It is necessary for the attentional preference or accuracy of detection of object vibration to appear as a viewing behaviour-related activity. For perception and attention levels in the peripheral field of vision, metrics of eye movement such as rate of microsaccade (MS) are often introduced [14–16]. Since the MS rate represents a high level of information processing activity, task performance can be evaluated using this metric [17].

Generally, experimental evaluation of these complicated functions does not seem to be easy to analyse using conventional statistics tests such as frequentest

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statistics, as the number of trials per participant is limited. Recently, a statistical modelling technique including Markov chain sampling was used to provide another solution, even for the measurement of temporal data such as biological signals [18–20]. If a hierarchical model between observed visual attention and latent resource activity could be defined, changes in the level of visual attention as temporal events in eye tracking may make it possible to extract this latent resource using statistical modelling technique.

This paper examines the possibility of estimating the directional bias of the peripheral field of vision using the appearance of MS rates and behavioural responses. Directional biases of awareness were observed using a perceptual experiment based on paying attention to dual tasks in the central and peripheral fields of vision. Estimation of the level of attention was conducted using a hierarchical modelling technique. In particular, temporal changes in attention are extracted using estimated parameters. The following topics will be addressed in this paper.

1. Visual attention characteristics of the peripheral field of vision are estimated and analysed using both eye movements and perceptual responses.

2. Temporal attention levels are estimated using MS rate measurements, and directional bias is examined using response reactions.

3. Estimated parameters of the converged model are analysed to extract characteristics of directional bias or response features while the temporal change in attentional level is evaluated.

2. Related works

2.1. Possible applications of peripheral field of vision

Peripheral cues have been studied, as peripheral stimuli such as Posner tasks and derivative tasks can provide a benefit to information processing as a covert attention [21–23]. In these studies, behaviour related to paying attention and the concomitant spatial and temporal changes in the results of experiments in response to the response conditions during experiments are discussed [6, 8, 24]. The phenomena which are related to the roles of the central and peripheral field of vision have been discussed in order to understand the viewing mechanisms [5]. These functions play a major role in complicated tasks such as driving a car or playing video games, where general purpose viewing ability is measured as UFOV (useful field of view) [2, 6, 25].

The viewing characteristics of displays vary, and thus human peripheral attention distribution and attention paying behaviour studies using displays have been conducted in order to develop better display interfaces [26, 27]. Viewing attention in the peripheral field of vision has also been studied in the field of research of human computer interaction [7, 28]. Recently, viewing behaviours in the peripheral field of vision was considered during the development of head mounted display (HMD) system. Visual perception ability and its possible application to improving display utilisation has been studied [29–32]. Some of these studies also measure eye movement in order to extend information displays using the peripheral field of vision [10, 11, 33]. The dynamic characteristics of viewing behaviour were also studied in detail when information was shown to both central and peripheral field of vision [12, 34].

2.2. Eye movement and the peripheral field of vision

In addition to using activity in the field of vision [35] and visual cortex activity [36], attention levels can be evaluated using features of eye movements [37, 38] The peripheral field of vision has been used to study attention levels in computer vision systems [9]. In addition to conventional eye movement, microsaccade behaviour has often been discussed as a key metric of attention-paying activities such as fixation on a particular point in the peripheral field of view [39–42]. Since microsaccade rates reflect brain activity, microsaccades can be an index of attention-paying activity [43–46]. The relationships between microsaccade rate mitigation and peripheral target appearance may provide some evidence of the existence of a human visual information processing mechanism [42]. Visual attention is driven by attention-paying activity in the central and peripheral fields of vision, and affects microsaccade rates [44, 47]. However, the detailed mechanism of human visual information processing and attentions remains unclear in regard to the design of an effective functional display, and thus changes in temporal attention levels should be examined.

2.3. Dominance of the field of vision

Eye movement is driven by bottom-up factors of image features such as saliency [48]. Visual attention contributions are often considered for attention payment and viewing behaviour [49]. Viewing behaviour and eye movement patterns are often explained using these approaches. These factors reduce gradually during observation and the fixation point becomes centralised, however [50]. Of course, attention distribution may not be explained by simple phenomena. Behavioural responses are influenced by various visual or spatial factors [51, 52]. On the other hand, a well-known practical bias is reading direction, which is based on left-to-right scanning behaviour [53]. Similar dominance has been observed during the viewing of faces in several experiments [54, 55]. One possible reason given is the

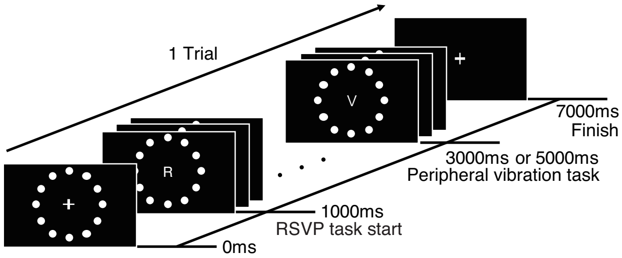

Figure 1. Presentation time flowchart

imbalance of activation of the left and right hemispheres [56, 57].

These results may suggest asymmetries in viewing behaviour. The results of tests of attention distribution in viewing areas and toward objects shows a leftward dominance in asymmetric performance [58]. This result should be confirmed in this paper.

2.4. Bayesian inference approach

Most psychological experiments are based on a rigid experimental design which is structured in advance to extract statistical differences in order to examine hypothesis. Both the influence of repeated measurement in order to obtain stable responses and the individual difference of participants should be considered in the analysis. Therefore, innovative measurement techniques and paradigms are required to obtain more accurate data. Recently, the Bayesian inference approach has provided some advantages to obtaining robust solutions, even in cases where the number of measurements is limited or the measurements include artefacts [18, 20, 59]. Also, several calculation platforms have been developed which allow the introduction of various types of data [60–62].

The Bayesian inference approach technique can be applied to data sets gathered in advance. The conventional experimental paradigms have been re-analysed and new evidence of mental mechanisms have been extracted [63, 64]. Also, temporal changes in observation can be analysed using this approach [65].

3. Method

Experimental design and measurement procedures to measure viewer's responses are as follows.

3.1. Experimental procedure

The experimental design was based on previous studies [12]. Temporal visual attention levels were observed using an experiment which presented central and peripheral cues, a timecourse of presenting visual stimuli is shown in Figure 1 [66]. Some experimental conditions were updated in order to focus on the level of attention in comparison with the responses of the previous experiment [13]. Twelve small dots (size: 2deg) were placed in a circle (radius: 25deg angle of vision), one every 30deg, and one of the dots was vibrated within a radius of 1px (0.054deg) at 2 frequencies (10 and 15 Hz). The colour of the dots was white and the background was black. The experimental task consisted of a dual task, namely the detection of an object vibrating in the peripheral field of vision, while searching in the central field of vision for numerals. The experiment's tasks are defined as the central vision task and the peripheral vision task.

The central field of vision viewing task is based on a RSVP (Rapid Serial Visual Presentation) task where the object is to find two or three single numeral targets from among randomised sequences of letters of the alphabet. The visual angle of the letters is 2.5deg. The numerals appeared at around 2000 and 4000ms, with the option to display them again at 6000ms. Therefore, the central task consisted of two levels of task difficulty. One of the peripheral dots vibrated at around 3000 and 5000ms, which allowed the two levels of difficulty of the task to be controlled. Stimulus onset timing was varied slightly around the specified times in order to avoid prediction of the appearance of the dots.

The stimuli were displayed on a 27 inch LCD monitor (EIZO: EV 2736W-Z), with subjects positioned 330mm away from the monitor, seated, and using a chin rest. The eye movements of both eyes were measured at 400Hz using an eye tracker (Arrington:BCU400). MS rates for every 500ms period were extracted from the eye movement observations of both eyes using the Microsaccade toolbox [67]. The algorithm of detecting MS is based on measured velocity and duration of saccades, synchronised MSs on both eyes are selected finally. The observed frequency (y_t) for every 100ms period was calculated.

The experimental tasks were explained to all subjects, with the central field of vision task of viewing displays of characters given as the focus of the four trial exercises. Regarding the design of the experiment, the number of trials was 96 (12 directions × 2 kinds of targets × 2 timings × 2 frequencies), and these were divided into three sets, consisting of 32 trials with 10 minute breaks between each set.

Subjects were asked to report orally the direction of vibration of the dot in relation to the centre. Five paid participants, who were aged 23±1 and who possessed sufficient visual acuity and colour perception, took part in this experiment in order to confirm the phenomenon from the previous experiment [13]. Most phenomena have already been confirmed using a number of paid participants in experiments which were conducted previously. The experimental conditions, including the number of measurement trials, were based a design that was used to produce the results of our previous experiment [13].

All subjects participated in an instruction session before the experiment and provided their written consent in order to participate. The procedure was approved by an ethics committee at Tokyo Institute of Technology (#2019052).

3.2. Observed responses

Behavioural responses: . The behavioural attention level in the designated peripheral vision regions was evaluated using a variable vibration detection rate and was based on oral responses.

The mean correct detection rates at the two frequency levels (10Hz and 15Hz) are illustrated in Figure 2. Here, the points around the circle show the directional position of the vibration presented, and the points on the polar scale show the rate of correct detection as a percentage. Detection rates at two vibration frequencies (10Hz and 15Hz) are illustrated. When vibrations were presented at 10Hz, the detection rate of most directions was almost perfect, except for the completely vertical up and down directions where the rates were above 80%. When the vibration frequency was increased to 15Hz, detection rates fall to zero in most directions except toward the region on the left. These results confirm that the frequency of vibration influenced the vibration detection rate [66].

Ocular responses: . The mean rates for correct and incorrect responses having 95% confidence intervals (CI) are summarised in Figure 6. There are some significant differences (effect size=small) in MS rates between responses, and the changes in levels of attention are unclear.

4. Results of observer's responses

In the following analysis, some irregular eye tracking data was omitted, such as eye movement 10 degrees or more away from the central fixation point. As the overall error rates of reporting numeral targets deviated 7.9∼22.1%, the task difficulty setting might work well in comparison with the task difficulty of our previous study [13].

4.1. Behavioural responses

The behavioural attention level in the regions of the peripheral field of view was measured using a vibration detection rate which was based on oral responses. The mean detection rates at the two frequency levels (10 and 15Hz) are illustrated in Figure 2 using a polar axis format. Since the rates for the upper and lower regions decrease when the frequency of vibration is increased, the effect of the frequency change is confirmed.

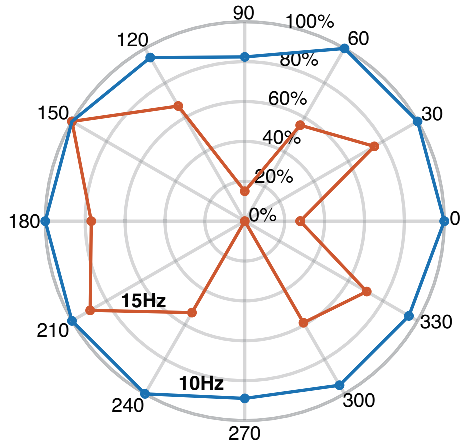

Figure 2. Mean detection rates for peripheral tasks using polar coordinates.

Modelling equations: . As behavioural detection ability may involve various factors, the contribution of the factors was analysed using the hierarchical Bayesian modelling technique [13, 68, 69], as shown in the following four models. In this study, the effectiveness of the three parameters in Table 1 are considered. As noted in the experimental procedure, the number of participants and measurement trials are limited. The number of samplings was controlled to obtain a converged solution in order to compensate for the insufficient volume of measured data produced during model optimisation.

1. Fundamental model

   Here, the mean detection rate (θ) is hypothesised as a summation of observed binary data Y (correct/incorrect responses), as shown in Equation (1). The rate θ can be noted using a logit link function and the summation of the two vibration frequencies (F) with intercept (β_1) as a fixed factor, and the twelve directional effects (PO) as variable factors. The individual effect (rID) is added in Equation (2) in order to represent the differences of each individual subject [13]. The order effect was ignored since the values are too small.

$$Y \sim Bernoulli\,(\theta) \tag{1}$$

$$logit\,(\theta) = \beta_1 \times F + PO + rID \tag{2}$$

2. Effect of correctness on the central task

   The detection rate can be updated by influencing the performance of the central task using the parameter $Ctask\_Effect$. This parameter correlates with the parameter $C\_CorrectFlag$ which gives the correct central task response, as shown in Equation (3). The parameter $Ctask\_Effect$ in Equation (4) is defined as a Normal distribution

Table 1. Parameter estimation

Parameter label	N of parameters	Description	Probability Distribution
$Ctask\_Effect$	1	Correctness of the central task	$Normal\,(0, sCEff)$
$Ctask\_Pattern$	2	Task difficulty of the central task	$Normal\,(0, sCPatt)$
$Ptask\_Pattern$	2	Timing of peripheral task	$Normal\,(0, sPPatt)$

with mean 0 and $sCEff$ as SD.

$$logit\,(\theta) = \beta_1 \times F + PO + rID + Ctask\_Effect \times C\_CorrectFlag \quad (3)$$

$$Ctask\_Effect \sim Normal\,(0, sCEff) \quad (4)$$

3. Effect of the number of targets on the central task

   The effect is assigned to the above Equation (2) using the parameter $Ctask\_Pattern$, as shown in Equation (5). The parameter follows a Normal distribution with two mean values (6) in response to display timings, as shown in Equation (6), and is defined as a Normal distribution with mean 0 and $sCPatt$ as SD.

$$logit\,(\theta) = \beta_1 \times F + PO + rID + CtaskPattern \quad (5)$$

$$CtaskPattern_c \sim Normal\,(0, sCPatt)\,(c = 1, 2) \quad (6)$$

4. Effect of timing on peripheral vibration

   The effect is also assigned to the above Equation (2) using the parameter $Ptask\_Pattern$, as shown in Equation (7). The parameter $Ptask\_Pattern$ also deviates between intervals when vibration occurs, as shown in equation (8), and is defined as a Normal distribution with mean 0 and $sPPatt$ as SD.

$$logit\,(\theta) = \beta_1 \times F + PO + rID + PtaskPattern \quad (7)$$

$$PtaskPattern_p \sim Normal\,(0, sPPatt)\,(p = 1, 2) \quad (8)$$

Estimation and model selection. Model parameters were estimated using the Markov Chain Monte Carlo (MCMC) technique, and an EAP (estimated as a posterior) estimation was used to calculate the mean of the parameter samples obtained from between 500 and 4000 iteration periods in each of the four independent MCMC chains. The convergence of the calculation was evaluated using the index ($\widehat{R} \leq 1.1$). The model fitness was evaluated using an index of WAIC. In the results, Equation (2) (WAIC=280.8) and Equation (3) (WAIC=277.2) were optimised, but the other equations were not. In regard to WAIC values, the model based on Equation (3) is the best one. Therefore, the two factors of the number of targets in the central field of vision task and the timing of the peripheral vibrations cannot be confirmed. As a result, these factors may be ignored in the following analysis. Detection ability in the regions of the peripheral field of vision using Equation (3) is discussed in the following sections.

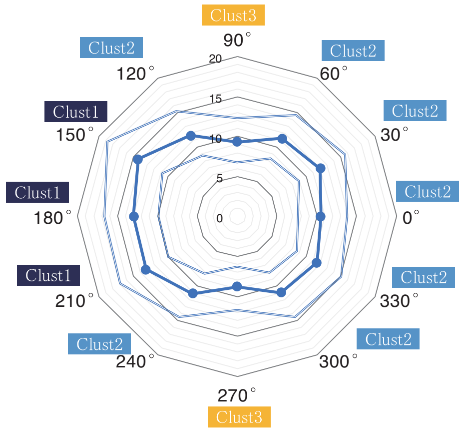

Figure 3. Results of cluster analysis of estimates (PO)

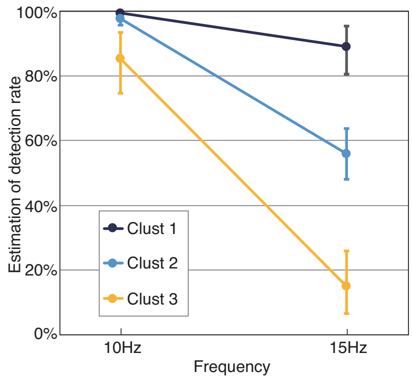

Figure 4. Frequency dependency of fields of view ($PClust$)

Detection ability analysis using estimated parameters: . The effectiveness of the parameters for individual factor (rID), intercept for vibration frequency (β_1) and the correctness of responses in the central field of vision task ($Ctask\_Effect$) are confirmed, as the changes are in response to behavioural reactions.

The results of posterior distribution analysis of directional parameter PO are summarised in Figure 3 as a solid line using a polar axis format map. The fine line indicates a confidence interval of 95%. In comparison with Figure 2, Figure 3 shows a plausible response, thus

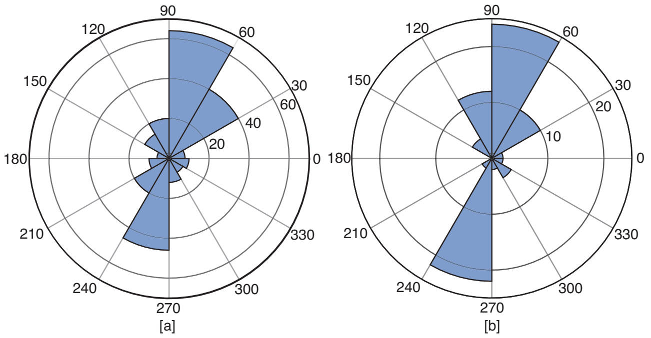

Figure 5. Directional distributions of differentials by fixation point: [a] vibration detection, [b] vibration not detected

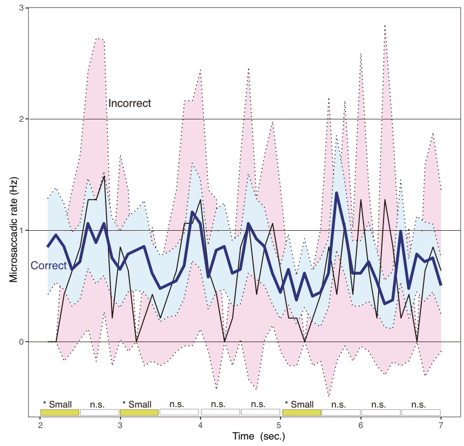

Figure 6. Mean MS rates of correct and incorrect responses during a trial

the effectiveness of the estimation has been confirmed. In order to extract the similarities of the directional responses, cluster analysis was applied to the features of the estimated parameter PO using the k-means method, to the values of the means and SDs, and to the values of the confidence intervals. In the results, three clusters were extracted, and these are labelled as Clust1∼Clust3 in Figure 3. The fundamental tendency is similar to the results of the previous study [13].

The vibration frequency reaction performance of the three clusters is summarised in Figure 4. The horizontal axis represents the frequency (10 and 15Hz), and the vertical axis represents the estimated detection rate parameter. Estimated parameter means and standard errors for the three clusters are illustrated in the figure. For $Clust3$, detection performance decreases with vibration frequency, which suggests that performance changes according to the peripheral region cluster. Performance is the highest when the stimulus is presented in a leftward direction, as is shown in Figure 4. Clust1 on the left side shows the highest correct rates, which may have been caused by the tendency to view the left area of a document first while reading, which is known as reading bias [53–55].

4.2. Distribution of fixation points

The influence of peripheral vibration on eye movement while viewing the central field of vision task was examined in order to measure the awareness capability of the peripheral field of vision. Fixation point differentials of before and after introduction of the peripheral vibration stimulus were measured. The initial point was set to means of fixation points before vibration occurred, and the final point was set to the mean points of the viewer's responses, when the subjects became aware of the peripheral stimulus. Otherwise, the duration was set to 582msec. as the overall mean of reaction time.

Frequency of differential direction for vibration detection [a] and condition of unconsciousness of the stimulus [b] are summarised in Figure 5, using a polar axis format. The figure suggests that eye movement is observed mainly as a series of vertical shifts. As Figure 5 shows, the directional frequency patterns seem similar. Using cross correlation, the coefficient for the condition with and without awareness of the peripheral stimulu is $r = 0.71$. Therefore, observed eye movements under both conditions were mostly vertical oscillations, and thus viewers did not pay attention to the peripheral field of vision stimuli.

5. Modelling for Microsaccades

5.1. MS rates in regions of the peripheral field of vision

In order to extract the procedure used to process visual information and to evaluate changes in viewer's attention, another statistical model of the MS rate measurements was created in regard to the behavioural model mentioned above. Here, latent activity as shown by the MS rates is summarised in a trial, as shown in Figure 6.

The MS rate may be influenced by the clusters in the peripheral regions, and these changes are summarised in Figures 8 ∼ 10. The peaks of the rates shifted around the early stage in Class1, and the peaks are delayed in both Class2 and Class3. These responses may be affected by the viewer's latent activity.

Model definition for Microsaccades: . In regards to observations of latent activity using MSs, a variable for attention resource was introduced [70]. An outline diagram of the modelling presentation is shown in Figure 7. During observations, MS rates variations may be the result of the changes in the level of human latent attention resources, which are updated using the level of attention. These dynamics are noted as variables and equational calculations, as follows.

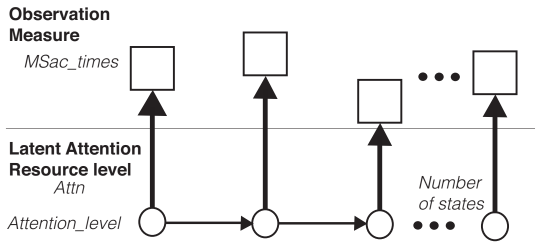

Figure 7. A diagram of a hierarchical model

Attention resource $Attn$ is a summation of the latent activity $Attention\_level$ and intercept variables such as $Response$, $Clust$ and rID. $Response$ represents the bias of correct or incorrect responses, and $Clust$ represents the peripheral position bias corresponding with the three clusters of positions in Figure 3. rID represents the factor for individual participants. $Attention\_level$ is an original measurement of MSs, and is shown in Figure 16 using a state model format. MS rate $MSac_{times}$ is noted as a state model using Poisson distribution. The observation period for modelling is set to 5 seconds, from 2 to 7sec. after the initial central task. Originally, the MS rate was measured every 100ms (0.1sec.), however the above parameters could not be introduced into the model. Patterns of the temporal re-sampled MS rates were compared in order to evaluate the contributions of response correctness and peripheral regions of stimulus presented [66]. Since the number of states might be too high for the estimation of parameters, some re-sampling processes were conducted during optimisation, as noted in the following calculations.

- Latent Attention Resource level:

  $$Attn = Attention\_level + Response + Clust + rID$$

  State Model:

  $$Attention\_level_i \sim normal(Attention\_level_{i-1}, \sigma_s)$$

- Microsaccade rate:

  $$\lambda = exp(\mu_{noise})$$

  Observation Model:

  $$\mu_{noise} \sim normal(Attn, \sigma_{noise})$$

  $$MSac_{times} \sim Poisson(\lambda)$$

Model estimations: . All parameters were estimated based on observed MS rates using the above models and the MCMC technique. The data from 11000 iterations with 500 burn-in lengths was sampled. All converged models were evaluated, and the ones which were optimised were selected using a fitness index such as $\hat{R}$, as well as using the above model. Parameters were estimated for all subjects and trials.

Means and CIs of the estimated attention levels $Attention\_level$ are summarised in 10 time bins (2~7 sec.), as shown in Figure 11. The time bins were reduced to 10 in order to obtain optimally converged results from the 50 time bins. Therefore, each time bin corresponds to responses made every 0.5 seconds. The level increases gradually until the 7th bin (5.5 sec.) at perception of the second peripheral stimulus. The changes in internal levels of attention are also displayed in the figure.

Correct and incorrect $Response$ parameters are summarised as distributions in Figure 12. $Clust$ is summarised in Figure 13, and participant's parameter rIDs are summarised in Figure 14. Though the differences between the categories seem small for $Responses$ and $Clust$, for participant's parameters rID the differences between individuals are shown clearly.

5.2. Estimation of attention states

Another attention resource variable $Attn$ is calculated as a summation of attention levels ($Attention\_level$), correct and incorrect responses ($Response$), position factors presented as a cluster ($Clust$), and individual factors (rID). The estimated statistics for correct and incorrect responses are illustrated using means and CIs, as shown in Figure 16. The horizontal axis represents time course in seconds during the trial, and the vertical axis represents latent attention resources. The attention resource $Attn$ may display the resources remaining for information processing. Therefore, dropped periods show a high mental workload demand. Attention levels dropped just after the appearance of stimuli at 3 and 5 sec., due to the introduction of the stimuli. The levels between correct and incorrect responses are compared using a t-test. In the results, there are significant differences, and the effect sizes are "Medium" for all time bins [71].

As Figure 16 shows, the levels for correct responses are significantly higher than for incorrect responses. The results suggest that, for any cluster, more resources are used for incorrect response reactions to the stimuli which were presented during the trial sessions. This means that viewers have used a large amount of their attention resources, but the task is not completed as the situation is out of the ordinary. In particular, the levels dropped just after the appearance of stimuli at 3 and 5 sec., as specific processing resources were required for incorrect reactions made in response to the occurrence of the peripheral vibration cue.

In addition, measurements of attention resource $Attn$ in correct responses are classified into 3 clusters

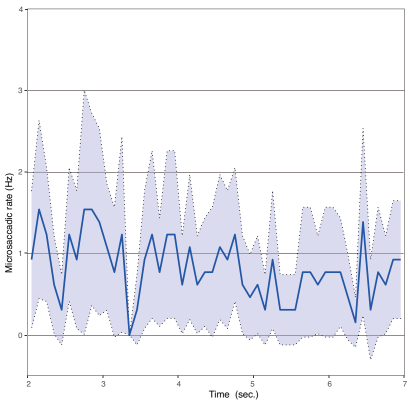

Figure 8. MS rates (Hz) in Clust1

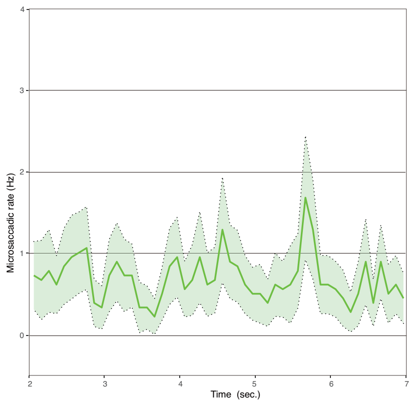

Figure 9. MS rates (Hz) in Clust2

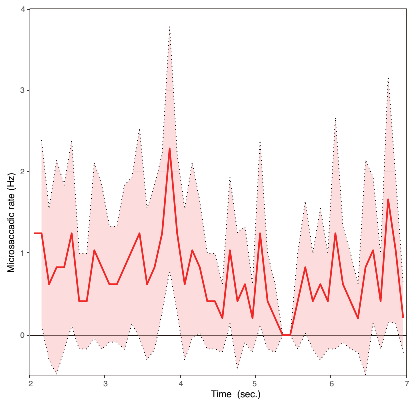

Figure 10. MS rates (Hz) in Clust3

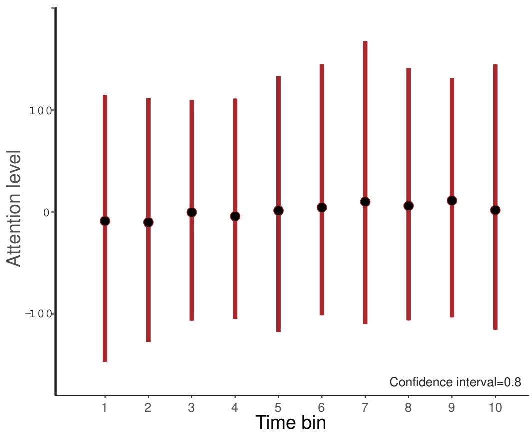

Figure 11. Estimation of attention levels presented in the state model ($Attention\_level_{i=1,...,10}$).

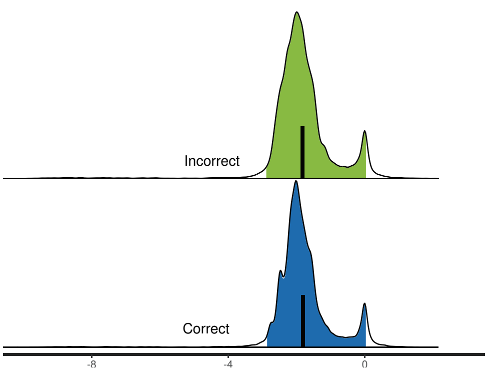

Figure 12. Parameter distributions of *Response*.

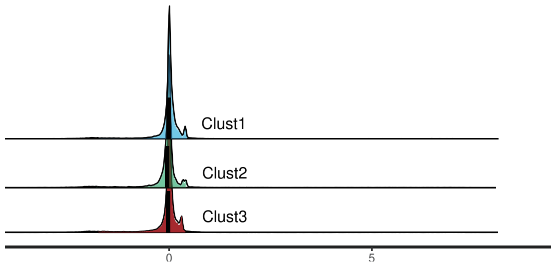

Figure 13. Parameter distributions of *Clust*.

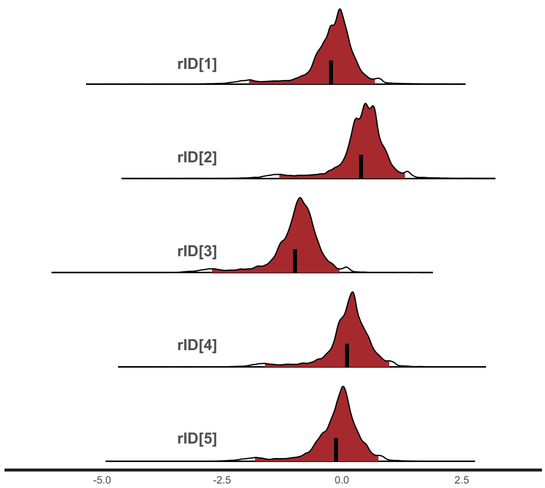

Figure 14. Parameter distributions of *rID*.

in order to evaluate the effect of the position of the peripheral vibration during the detection of stimuli. Attention resources for correct responses are summarised as three clusters in the time bins in Figure 17 using the same format as in Figure 16 by illustrating the means and CIs. The three plots represent the means of Clust1∼Clust3 from left to right. The differences of the three clusters are not significant using one-way ANOVA ($F(2, 288) = 2.21, p = 0.11$), and the effect size is "Small" ($\eta^2 = 0.02$). In regard to the order of means for levels of attention resources remaining, peripheral stimuli on $Clust1$ require a lower level of resources and the stimuli on $Clust3$ require a higher level of resources.

Incorrect responses are introduced to the comparison of attention resources of the three clusters, and the results are summarised in Figure 18. For correct

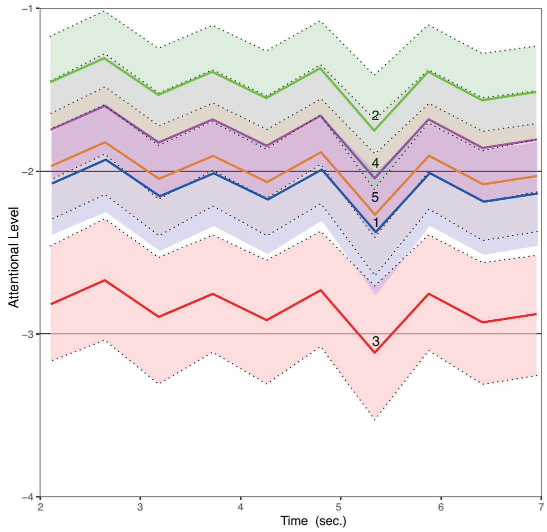

Figure 15. Changes in latent attention resources ($Attn$) between participants.

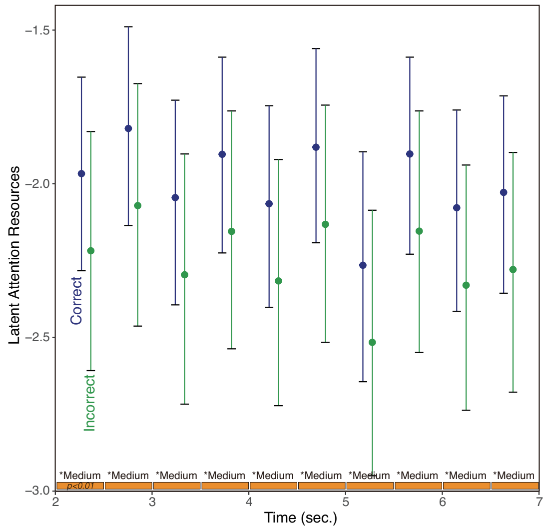

Figure 16. Estimation of latent attention resources ($Attn$) of correct and incorrect responses. The effect size is medium due to significant differences in the resources in each time bin.

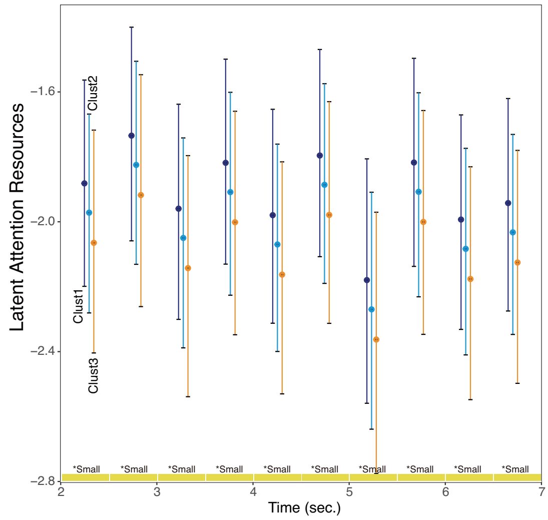

Figure 17. Estimation of latent attention resources ($Attn$) of the three clusters (from left to right: Clust1∼Clust3 for correct responses). The effect size shows small due to the significant differences in resources of the three clusters for each condition.

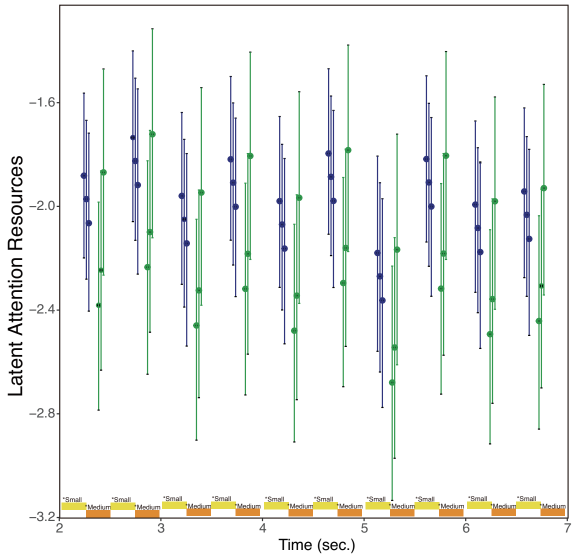

Figure 18. Estimation of latent attention resources ($Attn$) of the three clusters (from left to right: Clust1∼Clust3 for correct and incorrect responses in each time bin). The significant differences of the effect sizes of the resources of three clusters for each condition are shown.

responses, the order of incorrect responses of means for levels of resources is reversed Two-way ANOVA is applied to attention resources for both responses in order to extract analysed factors for responses and clusters. The result show that the factor for type of response is significant ($F(1, 322) = 12.0, p < 0.01; \eta^2 = 0.02$, Effectsize: Small), and that their interaction is also significant ($F(2, 332) = 3.5, p < 0.05; \eta^2 = 0.02$). For incorrect responses, the factor of clusters is not significant ($F(2, 44) = 2.2, p = 0.12; \eta^2 = 0.09$, Effectsize: Medium). The mean levels for $Clust2$ and $Clust3$ for incorrect responses are lower than for other conditions, but the mean levels for $Clust3$ are comparable with the means for $Clust1$ for correct responses. In the experiment, the number of incorrect responses was relatively small, and during some trials a few MSs were observed in $Clust1$. The estimation model may provide lower values, causing calculations using missing responses. On the other hand, the high estimation for incorrect responses in $Clust3$ may come from cases of missed stimulus due to not having paid enough attention. It may be possible to remain at a comparable level of correct responses. The estimated attention level of incorrect responses in $Clus3$ might be irregular, since participants did not recognise the stimulus well.

6. Discussion

Both behavioural responses and visual attention levels based on MS rates of the peripheral and central fields of vision during a dual task are compared in order to extract internal visual processing information during an experiment [13, 66].

The rates of detection of peripheral stimulus vibration as a measurement of behavioural response performance are summarised in Figure 2. The bias of the positions of the peripheral stimulus toward behavioural response performance was estimated using a modelling technique, and the distribution was summarised in Figure 3. In regard to the distribution of behavioural responses, the dominance of the left side was confirmed for the rate of correct responses. Though the visual stimulus was presented at set positions around a circle, the locations of correct responses were distributed along a horizontal ellipse which has a protrusion on the left side. Initially, this spatial bias might have been influenced by factors related to an issue with the setup of the experiment, the phenomenon was confirmed in additional experiments. In regard to the previous studies, the dominance of the left side field of view is suggested by the effect of the direction in which the text is read, which is from the left side of the document display [53–55]. Some of the benefit of the bias which was introduced is also used to pay greater attention to the field of view on the left side. The reason for a different factor for the negative bias of the top and bottom positions of the field of view may be due to the shape of the field of view, but the factors regarding the setup of the experiment may also influence viewing behaviour.

The intention of this research is the confirmation of whether the behavioural bias synchronises the sensitivity of peripheral visual attention using microsaccade rates. As the level of visual attention changes during trials, the factor of the position of the visual stimulus in the peripheral field of vision needs to be extracted and evaluated. Using a hierarchical Bayesian modelling technique, the contribution to the three cluster of position in the peripheral field of vision was evaluated. Figure 16 shows that correct responses require more attention resources than do incorrect responses. The attention resources for correct responses required in each of the three clusters are compared in Figure 17. The resources required for $Clust1$ are less than those required for $Clust2$ and $Clust3$. In particular, the reduction of resources required around peripheral stimulus onset is significant at around 3000 and 5000ms.

However, the above discussion is based on estimation made using only a small quantity of microsaccade rates, and excluding any physiological evidence. One possible estimation to be considered is the direction position bias in the peripheral field of vision. In order to discuss the matter further, multiple biological measurements should be introduced. Conventional physiological measurements should certainly be employed to examine this phenomenon. In addtional, the number of estimations of incorrect responses was extraodinary, as the number of responses was small and the proper performance of the task might not have been confirmed well. The condition of paying attention during incorrect responses will be another subject of our further study.

In this work, microsaccade rates were evaluated every 500ms in order to reduce computational cost and the possibility of convergence. For a more detailed analysis, an assessment at a higher eye tracking frequency should be conducted. These approaches will be subjects of our further study.

7. Conclusion

This paper examines the directional bias of the peripheral field of vision during responses made in a dual task experiment, using a modelling technique applied to behavioural responses and MS rates.

First, modelling the accuracy of behavioural responses allows the biases of the advantage of the field of vision on the left side, and the influence of the field of view at the top and bottom to be extracted. In order to extract latent attention levels during responses, another modelling technique was applied to estimate attention resources using MS rates as indices of mental processing. The parameters of the model suggested that changes in attention levels are required while responses are taking place. Also, the temporal effects of the directional bias of the peripheral field of vision on correct and incorrect responses were extracted and compared. Peripheral stimulus onset also affected latent attention levels.

In order to optimise the model, the MS rate sampling rate was reduced. Analysis using higher intervals of measurement and a more robust modelling technique will be subjects of our further study.

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References

[1] Underwood, G. (2005) *Cognitive Processes in Eye Guidance* (Oxford, UK: Oxford University Press).

[2] Wood, J.M. and Owsley, C. (2014) Gerontology viewpoint: Useful field of view test. *Gerontology* **60**(4): 315–318.

[3] Klein, C. and Ettinger, U. (2019) *Eye Movement Research, An Introduction to its Scientific Foundations and Applications* (Springer Nature Switzerland AG).

[4] Smith, A.T. (1994) The detection of second-order motion. In Smith, A.T. and Snowden, R.J. [eds.] *Visual Detection of Motion* (London, UK: Academic Press), 145–176.

[5] Lleras, A., Buetti, S. and Xu, Z.J. (2022) Incorporating the properties of peripheral vision into theories of visual search. *Nature Reviews Psychology* **1**: 590–604.

[6] Green, C.S. and Bavelier, D. (2006) Effect of action video games on the spatial distribution of visuospatial attention. *Journal Experimental Psychology, Human perception performance* **32**(6): 1465–1478.

[7] Dingler, T. and Schmidt, A. (2016) Peripheral displays to support human cognition. In Bakker, S., Hausen, D. and Selker, T. [eds.] *Peripheral Interaction –Challenges and Opportunities for HCI in the periphery of Attention–* (Switzerland: Springer International Publishing AG Switzerland), 167–182.

[8] Klein, R.M., Reichertz, M., Christie, J., Wong, J. and Maycock, B. (2019) On the roles of central and peripheral vision in the extraction of material and form from a scene. *Attention, Perception, & Psychophysics* **81**: 1209–1219.

[9] Sun, Y., Fisher, R., Wang, F. and Gomes, H.M. (2008) A computer vision model for visual-object-based attention and eye movements. *Computer vision and image understanding* **112**: 126–142.

[10] Ishiguro, Y. and Rekimoto, J. (2012) Peripheral vision annotation: Noninterference information presentation method by using gaze information. *Journal of IPSJ* **53**(4): 1328–1337.

[11] Kishishita, N., Orlosky, J., Kiyokawa, K., Mashita, T. and Tekemura, H. (2014) Investigation on the peripheral visual field for information display with wide-view see-through hmds. *Transactions of VRSJ* **19**(2): 121–130.

[12] Shimura, M., Suzuki, H., Shimomura, Y. and Katuura, T. (2015) Perception of visual motions stimulation in peripheral vision during eye fixation. *Japan Journal of Physiology and Anthropology* **20**(2): 95–102.

[13] Ueno, T. and Nakayama, M. (2021) Influence of peripheral vibration stimulus on viewing and response actions. In *Proceedings of ICPR2020 (ETTAC2020)* (Milan, Italy: Springer): 1–8.

[14] Kashihara, K., Okanoya, K. and Kawai, N. (2014) Emotional attention modulates microsaccadic rate and direction. *Psychological Research* **78**: 166–179.

[15] Dalmaso, M., Castelli, L., Scatturin, P. and Galfano, G. (2017) Working memory load modulates microsaccadic rate. *Journal of Vision* **17**(3): 1–12.

[16] Poletti, M. and Rucci, M. (2016) A compact field guide to the study of microsaccades: Challenges and functions. *Vision Research* **118**: 83–97.

[17] Krejtz, K., Duchowski, A.T., Niedzielska, A., Biele, C. and Krejtz, I. (2018) Eye tracking cognitive load using pupil diameter and microsaccades with fixed gaze. *PloS One* **13**: 1–23.

[18] Dienes, Z. and Mclatchie, N. (2018) Four reasons to prefer bayesian analyses over significance testing. *Psychonomic Bulletin & Review* **25**: 207–218.

[19] Parr, T., Rees, G. and Friston, K.J. (2018) Computational neuropsychology and bayesian inference. *frontiers in Human Neuroscience* **12**(61): 1–14.

[20] Nguyen, M.H., La, V.P., Le, T.T. and Vuong, Q.H. (2022) Introduction to bayesian mindsponge framework analytics: An innovative method for social and psychological research. *MethodsX* **9**(101808): 1–16.

[21] Posner, M.I. (1980) Orienting of attention. *Quarterly Journal of Experimental Psychology* **32**: 3–25.

[22] Carrasco, M. (2011) Visual attention: The past 25 years. *Vision Research* **51**: 1484–1525.

[23] Inoue, Y., Tanizawa, T., Utsumi, A., Susami, K., Kondo, T. and Takahashi, K. (2017) Visual attention control using peripheral vision stimulation. In *Proceedings of International Conference on Systems, Man, and Cybernetics (SMC)*: 1563–1568.

[24] Patrick, J.A., Roach, N.W. and McGraw, P.V. (2019) Temporal modulation imporves dynamic peripheral acuity. *Journal of Vision* **19(13)**(12): 1–19.

[25] Classen, S., Wang, Y., Crizzle, A.M., Winter, S.M. and Lanford, D.N. (2023) Predicting older driver on-road performance by means of the useful field of view and trial making test part B. *American Journal of Occupational Therapy* **67**: 574–582.

[26] Matthews, T., Ratternbury, T., Carter, S., Dey, A.K. and Mankoff, J. (2003) A peripheral display toolkit. In *Proceedings of UIST2003*: 1–10.

[27] Guzman, E.S.D., Yau, M., Gagliano, A., Park, A. and Dey, A.K. (2004) Exploring the design and use of peripheral displays of awareness information. In *Proceedings of CHI2004*: 1247–1250.

[28] Bakker, S., Hausen, D. and Selker, T. (2016) Introduction: Framing peripheral interaction. In Bakker, S., Hausen, D. and Selker, T. [eds.] *Peripheral Interaction – Challenges and Opportunities for HCI in the periphery of Attention–* (Switzerland: Springer International Publishing AG Switzerland), 167–182.

[29] Matthies, D.J.C., Haescher, M., Alm, R. and Urban, B. (2015) Properties of a peripheral head-mounted display. In *Proceedings of 17th International Conference on Human-Computer Interaction*: 1–6.

[30] Horiuchi, K., Ishihara, M. and Imanaka, K. (2017) The essential role of optical flow in the peripheral visual field for stable quiet standing: Evidence from the use of a head-mounted display. *PloS One* **12**: e0184552: 1–16.

[31] Abraham M, H., Kitson, A., Nguyen-Vo, T., Benko, H., Stuerzlinger, W. and Riecke, B.E. (2018) Investigating a sparse peripheral display in a head-mounted display for vr locomotion. In *Proceedings of 2018 IEEE Conference on Virtual Reality and 3D User Interfaces*: 571–572.

[32] Lee, J.H., Yeom, K. and Park, J.H. (2023) The effect of video see-through HMD on peripheral visual search performance. *IEEE Acess* **11**: 85184–85190.

[33] Richards, K., Mahalanobis, N., Kim, K., Schubert, R., Lee, M., Daher, S., Norouzi, N. *et al.* (2019) Analysis of peripheral vision and vibrotactile feedback during proximal search tasks with dynamic virtual entities in augmented reality. In *Proceedings of Symposium on Spetial User Interaction (SUI '19)*: 1–9.

[34] Matsui, K. and Nakamura, S. (2018) Influence on time evaluation by presenting visual stimulus in peripheral

vision. *Journal of IPSJ* **59**(3): 970–978.

[35] Kwak, Y., Hanning, N.M. and Carrasco, M. (2023) Presaccadic attention sharpens visual acuity. *Scientific Reports* **13**(2981): 1–11.

[36] Schwartz, S., Vuilleumier, P., Hutton, C., Maravita, A., Dolan, R.J. and Driver, J. (2005) Attention load and sensory competition in human vision: Modulation of fmri responses by load at fixation during task-irrelevant stimulation in the peripheral visual field. *Cerebral Cortex* **15**: 770–786.

[37] Moore, T. and Fallah, M. (2001) Control of eye movements and spatial attention. *PNAS* **98**(3): 1273–1276.

[38] Kowler, E. (2011) Eye movements: the past 25 years. *Vision Research* **51**: 1457–1483.

[39] Collewijn, H. and Kowler, E. (2008) The significance of microsaccades for vision and oculomotor control. *Journal of Vision* **8(14)**(20): 1–21.

[40] Raveendran, R.N., Krishnan, A.K. and Thompson, B. (2020) Reduced fixation stability induced by peripheral viewing does not contribute to crowding. *Journal of Vision* **20(10)**(3): 1–13.

[41] Hung, S.C., Barbot, A. and Carrasco, M. (2023) Visual perception learning modulates microsaccade rate and directionality. *Scientific Reports* **13**(16525): 1–13.

[42] Watamaniuk, S.N., Badler, J.B. and Heinen, S.J. (2023) Peripheral targets attenuate miniature eye movements during fixation. *Scientific Reports* **13**(7418): 1–10.

[43] Martinez-Conde, S., Macknik, S.L., Troncoso, X.G. and Dyar, T.A. (2006) Microsaccades counteract visual fading during fixation. *Nueron* **49**: 297–305.

[44] McCamy, M.B., Otero-Millan, J., Macknik, S.L., Yang, Y., Troncoso, X.G., Baer, S.M., Crook, S.M. *et al.* (2012) Microsaccadic efficacy and contribution to foveal and peripheral vision. *The Journal of Nueroscience* **32**(27): 9194–9204.

[45] Hafed, Z.M., Yoshida, M., Tian, X., Buonocore, A. and Malevich, T. (2021) Dissociable cortical and subcortical mechanisms for mediating the influences of visual cues on microsaccadic eye movements. *frontiers in Neural Circuits* **16**(638429): 1–18.

[46] Liu, B., Nobre, A.C. and van Ede, F. (2023) Microsaccades transiently lateralise EEG alpha activity. *Progress in Neurobiology* **224**: 102433.

[47] Shelchkova, N. and Poletti, M. (2020) Modulations of foveal vision associated with microsaccade preparation. *PNAS* **117**(20): 11178–11183.

[48] Itti, L. (2005) Quantifying the contribution of low-level saliency to human eye movements in dynamic scenes. *Visual Cognition* **12**(6): 1093–1123.

[49] Borji, A. (2013) State-of-the-art in visual attention modeling. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **35**(1): 185–207.

[50] Tatler, B.W. (2007) The central fixation bias in scene viewing: Selecting an optimal viewing position independently of motor biases and image feature distributions. *Journal of Vision* **7**(14): 4.1–17.

[51] Yu, G., Herman, J.P., Katz, L.N. and Krauzlis, R.J. (2022) Microsaccades as a marker not a cause for attention-related modulation. *eLife* **11**(e74168): 1–14.

[52] Yip, S.H. and Saunders, J.A. (2023) Restricting the distribution of visual attention reduces cybersickenss. *Cognitive Research: Principles and Implications* **8**(18): 1–18.

[53] Nicholls, M.E. and Roberts, G.R. (2002) Can free-viewing perceptual asymmetries be explained by scanning, pre-motor or attentional biases? *Cortex* **38**: 113–136.

[54] Butler, S., Gilchrist, I.D., Burt, D.M., Perrett, D.I., Jones, E. and Harvey, M. (2005) Are the perceptual biases found in chimeric face processing reflected in eye-movement patterns? *Neuropsychologia* **43**: 52–59.

[55] Leonards, U. and Scott-Samuel, N.E. (2005) Idiosyncratic initiation of saccadic face exploration in humans. *Vison Research* **45**: 2677–2684.

[56] Nicholls, M.E., Loftus, A., Mayer, K. and Mattingley, J.B. (2007) Things that go bump in the right: The effect of unimanual activity on rightward collisions. *Neuropychologia* **45**: 1122–1126.

[57] Nicholls, M.E., Loftus, A.M., Orr, C.A. and Barre, N. (2008) Rightward collisions and their association with pseudoneglect. *Brain and Cognition* **68**: 166–170.

[58] Klatt, S., Noël, B. and Schrödter, R. (2024) Attentional asymmetries in peripheral vision. *British Journal of Psychology* **115**(1): 40–50.

[59] Wagenmakers, E.J., Marsman, M., Jamil, T., Ly, A., Verhagen, J., Love, J., Selker, R. *et al.* (2018) Bayesian inference for psychology. part i: Theoretical advantages and practical ramifications. *Psychonomic Bulletin & Review* **25**: 35–57.

[60] Lee, M.D. (2011) How cognitive modeling can benefit from hierarchical Bayesian models. *Journal of Mathematical Psychology* **55**: 1–7.

[61] Haaf, J.M. and Rounder, J.N. (2017) Developing constraint in Bayesian mixed models. *Psychological Methods* **22**: 779–798.

[62] Sch onbrodt, F.D. and Wagenmakers, E.J. (2018) Bayes factor design analysis: Planning for compelling evidence. *Psychonomic Bulletin & Review* **25**: 128–142.

[63] Muto, H. and Nagai, M. (2020) Mental rotation of cubes with a snake face: The role of the human-body analogy revisited. *Visual Cognition* **28**: 106–111.

[64] Muto, H. (2021) Evidence for mixed processes in normal/mirror discrimination of rotated letters: A bayesian model comparison between single- and mixed-distribution models. *Japanese Psychological Research* **63**(3): 190–202.

[65] Dubiel, M., Nakayama, M. and Wang, X. (2023) Modelling attention levels with ocular responses in a speech-in-noise recall task. In *Proceedings of ACM Symposium on Eye Tracking Research & Applications 2023 (ETRA2023)* (ACM): 89:1–7. https://doi.org/10.1145/3588015.3589665.

[66] Ueno, T. and Nakayama, M. (2021) Estimation of visual attention using microsaccades in response to vibrations in the peripheral field of vision. In *Proceedings of ACM Symposium on Eye Tracking Research & Applications 2021 (ETRA2021)* (ACM): 1–6.

[67] Engbert, R., Sinn, P., Mergenthaler, K. and Trukenbrod, H. (2015), Microsaccade toolbox 0.9. http://read.psych.uni-potsdam.de.

[68] Kubo, T. (2012) *Introduction to statistical modelling for data analysis* (Tokyo, Japan: Iwanami Shoten).

[69] Nakayama, M. and Ueno, T. (2023) Latent attention resource estimation of peripheral visual stimuli using microsaccade frequency modelling. In *Proceedings of 27th International Conference on Information Visualisation (iV)* (IEEE): 142–147.

[70] Nakayama, M. and Ueno, T. (2023) Estimation of latent attention resources using microsaccade frequency during a dual task. In *Proceedings of ACM Symposium on Eye Tracking Research & Applications 2023 (ETRA2023)* (ACM): 41:1–2.

[71] Anderson, S.F., Kelly, K. and Maxwell, S.E. (2017) Sample-size planning for more accurate statistical power: A method adjusting sample effect sizes for publication bias and uncertainty. *Psychological Science* **28(11)**: 1547–1562.