Use of a customized vision model to analyze the effects of higher-order ocular aberrations and neural filtering on contrast threshold performance

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1. INTRODUCTION

Adaptive optics (AO) techniques have recently been applied to investigate the effects of ocular aberrations on visual performance [1–5]. The studies mainly focused on high luminance vision and highlighted the benefit that could be gained in visual performance when correcting for higher-order (HO) aberrations. The work presented here was driven by recent experimental results showing that at low light levels the drop in neural contrast sensitivity moderates the effect of higher-order optical aberrations on visual performance for typical broad spectrum functional stimuli [5]. The test consisted in measuring the contrast threshold required to discriminate the orientation of a Landolt C subtending 15 arc min (the gap extended over 3 arc min), between four orthogonal orientations. The experimental apparatus was an AO vision simulator consisting mainly of a Shack–Hartmann wavefront sensor, a bimorph deformable mirror, and a projection simulator consisting mainly of a Shack–Hartmann wavefront sensor, a bimorph deformable mirror, and a projection simulator. Measurements of contrast sensitivity (inverse of contrast threshold) were carried out with and without correction of HO aberrations, to obtain what was called the AO visual benefit (the gain in contrast sensitivity with AO correction). The AO visual benefit was assessed for seven young subjects, under different conditions of pupil size and light level. The results showed that, as expected, the AO visual benefit increased when the pupil size, hence the amount of HO aberrations, increased [see Fig. 7 in [5]]. More interestingly, it was also found that for a fixed pupil size the benefit decreased as the light level was decreased [see Figs. 6 and 7 in [5]], implying that the drop in neural contrast sensitivity moderates the effect of the optical blur for this visual task. These results raised the importance of the combined effects of neural and optical limitations on functional visual tasks and how these vary with light level. They also indicated the need for a theoretical understanding based on a comprehensive and accurate modeling of the visual test.

Since the introduction of the contrast sensitivity function (CSF) by Campbell and Robson [6] the analysis of visual processes based on spatial frequency filters [7] has become widely established. This approach has not only been applied to the detection of gratings, but also to various visual tasks, including letter identification [8–11]. However, although many vision models now use the CSF, usually no separation is made between the optical transfer function (OTF) and the neural transfer function (NTF); furthermore the overall CSF commonly used is a generic function representing photopic conditions. Recent advances in ocular aberrometry [12] have enabled calculations of the effect of HO aberrations on image quality [13] through a simple modulation transfer function (MTF) derivation. AO techniques have also made it possible to measure the contrast sensitivity with and without ocular aberrations and compare it to simulations [1]. As for more complex visual tasks, Nestares et al. recently presented simulations of Snellen visual acuity with a Bayesian model observer that included individual data of MTF and NTF [11]. A customized ideal observer model was also shown to give a good prediction of visual acuity over a large set of evaluation data [14]. We followed a similar approach in disentangling neural and optical filtering in visual processes, with an emphasis on the change of the NTF with light level.

The dependence of the neural contrast sensitivity on light level is attributed to several factors. The signal-to-noise ratio (SNR) for detection is proportional to the square root of the intensity according to the DeVries–Rose
The aim of the present study was to gain a better understanding of how the optical and neural stages of visual processing combine in a range of natural light conditions and to provide a theoretical understanding for our laboratory measurements [5]. We based our analysis on an ideal-observer discrimination model for a multiclass functional visual task, with emphasis on the neural and optical transfer functions. We used a measure of separability as a tool to assess the relative observer performance in different optical and neural conditions reflecting the range of light levels encountered in everyday vision and compared the simulations to experimental results previously obtained. In Section 2, we detail the customized modeling approach and the separability measure. The numerical results are given in Section 3 and compared to the human-observer data from our laboratory experiments [5]. The discussion, in Section 4, focuses on the possible sources of numerical errors and discrepancy with the experimental data; an analysis based on the spatial frequency characteristics of the visual task is also given as an attempt to provide some explanation of the results. The conclusion is given in Section 5.

2. CUSTOMIZED IDEAL OBSERVER MODEL

Our model was developed following a classical approach for the discrimination task, as illustrated in Fig. 1. It includes several stages starting with the visual processes of the image seen by the observer (optical and neural filtering), yielding an image $s$. Noise is added to this image, yielding a data vector $g$ that is in turn used to produce a test statistic $t$ based on which the observer makes a decision to assign the data to a class. In the ideal-observer modeling approach, the observer compares the likelihood of the data under each hypothesis and chooses the class associated with the greatest likelihood. This section details the different stages and the performance of the model observer is defined with a separability measure.

**A. Visual Processes**

Our model is based on a spatial frequency analysis, with special attention paid to disentangling the optical and neural stages, similar to the work by Nestares et al. [11] and Watson and Ahumada [14]. In incoherent illumination an optical system is linear in intensity and the intensity of the image equals that of the object convolved with the intensity point-spread function (PSF). This is true only for a stationary (or isoplanatic) system, in which the optical degradation is independent of field angle. We will consider here stimuli subtending an angle less than 1°, which is commonly accepted to be within the eye's isoplanatic patch.

Similarly, the neural contrast sensitivity can be modeled as another filter applied to the retinal image. We used for this work a NTF constructed as a weighted sum of difference-of-Gaussians (DOG) functions. These band-pass profiles provide a good description of ganglion cell receptive fields [23]. A channelized model observer was also investigated (see Section 4), but the results reported here were obtained with the overall NTF. Several reports can be found in the literature on the effect of luminance on the CSF, showing a decrease as retinal illumination is decreased for a 2 mm fixed pupil [18,24], 3 mm fixed pupil [25], and natural pupils [25]. However, these results include the optical MTF as well as the neural NTF. In their study, Coletta and Sharma give the direct measurements of the neural NTF for two subjects and different light levels, using interferometric techniques to bypass the optics of the eye [26]. We used these particular data to construct two generic NTF curves, namely, for the photopic (300 Td) and low mesopic (0.3–1 Td) light levels (see Fig. 2). We wish to emphasize that the constructed curves are only a very crude approximation to known curves and processes. The important features that can be noticed in the figure are the reduction and the shift towards lower spatial frequencies of the neural contrast sensitivity from the photopic to the low mesopic light level.

The final image can be expressed in the Fourier domain as a vector...
where \( \tilde{I}_{\text{obj}}(u) \) is the Fourier transform of the object intensity, \( \text{OTF}(u) \) is the optical and \( \text{NTF}(u) \) is the neural transfer function.

### B. Multiclass Ideal Observer

The image obtained is corrupted by noise, which can have several sources, for example, light-dependent noise, neural noise, and fluctuations in the decision criterion. We will assume here that the noise can be represented by a single Gaussian vector \( \mathbf{n} \). Several studies have shown that human performance is well-predicted by an ideal observer in uncorrelated Gaussian noise; the human observer performance being scaled down by a factor (denoted efficiency) from the ideal observer performance [27]. Hence at this stage the data vector to be observed is \( \mathbf{g} = \mathbf{s} + \mathbf{n} \). The sum of the image vector and the noise vector. We wish to emphasize that the signal is here noise-free and that the only source of randomness in the model originates from neural processes. This is the so-called signal-known-exactly–background-known-exactly (SKE–BKE) problem [27].

For an \( L \)-class discrimination task, the observation consists in forming \( L \)-test statistics \( t_l \) corresponding to each class hypothesis \( H_l \); the observer assigns a given data set to a particular decision class based on the comparison between the test statistics. The ideal observer chooses the hypothesis \( H_l \) associated with the greatest likelihood (or conditional probability density function) of the data \( \text{pr}(\mathbf{g}|H_l) \). Assuming zero-mean independent noise, we can formulate the likelihood of the data vector as the product of its components

\[
\text{pr}(\mathbf{g}|H_l) = \left( \frac{1}{2\pi\sigma^2} \right)^{M/2} \prod_{m=1}^{M} \exp\left( -\frac{(g_m - s_{lm})^2}{2\sigma^2} \right),
\]

where \( M \) is the dimension of the data \( \mathbf{g} \), \( \sigma^2 \) is the variance of the noise on each component \( g_m \) of \( \mathbf{g} \), and \( s_{lm} \) is the \( m \)th component of the vector \( \mathbf{s}_l \) corresponding to the neural image of the object under hypothesis \( H_l \). Comparing the likelihood for each hypothesis is equivalent to comparing the logarithm of the likelihood, since that function is monotonic. After canceling the common terms for all hypotheses, the test statistics become

\[
t_l = -\sum_{m=1}^{M} (g_m - s_{lm})^2.
\]

### C. Model-Observer Performance

A figure of merit widely used to assess the performance of the model observer in a binary classification task is the test statistic SNR, which determines the separability of the classes

\[
\text{SNR}_l = \frac{\langle t_1 \rangle - \langle t_2 \rangle}{\sqrt{\frac{1}{2}(\sigma_1^2 + \sigma_2^2)}}.
\]

The discrimination between more than two classes of signals, such as letter discrimination, for example, requires a more complex figure of merit. We follow here the approach given by Barrett and Myers [27] who define the performance of a multiclass model observer with the Hotelling trace \( H_T^2 \); we introduce a separability measure

\[
S = \sqrt{4H_T^2} = \sqrt{4 \times \text{tr} [\mathbf{S}_1^\dagger \mathbf{S}_0]},
\]

where \( \text{tr} \) denotes the matrix trace, \( \mathbf{S}_1 \) is the interclass matrix that describes the average distance between the means of the distributions of the data under each hypothesis, and \( \mathbf{S}_0 \) is the intraclass scatter matrix that describes the average covariance matrix of the data,

\[
\begin{align*}
\mathbf{S}_1 &= \frac{1}{L} \sum_{l=1}^{L} \langle \mathbf{g}_l - \bar{\mathbf{g}}_l \rangle (\mathbf{g}_l - \bar{\mathbf{g}}_l)^\dagger, \\
\mathbf{S}_0 &= \frac{1}{L} \sum_{l=1}^{L} \langle (\mathbf{g} - \bar{\mathbf{g}}_l)(\mathbf{g} - \bar{\mathbf{g}}_l)^\dagger | H_l \rangle,
\end{align*}
\]

with \( \bar{\mathbf{g}}_l = \langle \mathbf{g}|H_l \rangle \) and \( \bar{\mathbf{g}} = (1/L) \sum_{l=1}^{L} \mathbf{g}_l \). For an \( L \)-alternative SKE–BKE problem, this gives

\[
S = \sqrt{\frac{4}{\sigma^2} \frac{1}{L} \sum_{l=1}^{L} ||\mathbf{s}_l - \bar{s}||^2}.
\]

The factor 4 and the square root were set so that the separability measure reduces to the SNR, for a binary classification task.

The separability measure is of particular interest for the assessment of the observer performance in a contrast threshold experiment. It can replace the intensive calculation of the observer decision for numerous random realizations of noise and contrast. Indeed, with \( S \) proportional to the contrast of the stimulus, one finds at the threshold \( c_T \) a threshold \( S_T \)

\[
S_T = S_0 \times c_T,
\]

with \( S_0 \) being the separability for unit contrast. \( S_0 \) is therefore proportional to the contrast sensitivity \( c \) measured experimentally. Furthermore, we have mentioned that the separability is equivalent to the SNR for a binary
problem. Under the assumption of normality of the test statistic, SNR, can be related to the percentage of correct responses in a two-alternative forced-choice test [27]. Hence model- and human-observer performance can easily be compared. A relation can also be found between the SNR and the percentage of correct responses of the model or human observer in the case of a multialternative location signal detection [28,29], which is mathematically equivalent to a multiclass signal discrimination task. Consistently, we assume that a similar relation holds between the multiclass separability measure and the percentage of correctness in a multiclass discrimination task. Therefore, for contrast thresholds measured with a fixed percentage of correct answers the ratio of separability measures for conditions 1 and 2 becomes equivalent to the ratio of contrast sensitivities in the two conditions

\[ \frac{(S_0)_{1}}{(S_0)_{2}} = \frac{(P_0/c)_{1}}{(P_0/c)_{2}} = \frac{cs_1}{cs_2}. \]  

(9)

D. Numerical Implementation

The model described above was applied to a four-alternative forced-choice contrast visual task that was tested experimentally [5]. The test consisted in measuring the contrast threshold required to discriminate the orientation of a Landolt C subtending 15 arc min (the gap extended over 3 arc min), between four orthogonal orientations. This test was developed and named the contrast acuity test by Chisholm et al. [30]. The stimulus spectrum contains a range of spatial frequencies typically encountered in normal functional visual tasks. As mentioned earlier, the customized model was developed to analyze the effect of the AO correction on the visual performance (here, contrast sensitivity) in different light regimes. In this paper, we compared the model-observer performance to the experimental data obtained for seven young subjects over a set of light levels ranging from 1000 to 0.3 Td, and pupil sizes of 6 mm for most of the subjects, and ranging from 3 to 6 mm for three subjects.

The individual wavefront aberration measurements performed during the experiments were directly used in the calculations, as detailed by Nestares et al. [11]. The PSF was computed as the normalized squared modulus of the Fourier transform of the pupil function \( P \)

\[ \text{PSF}(x,y) = \left| \text{FT}(P(x,y)) \right|^2. \]  

(10)

The coordinates \((x,y)\) in the image plane are related to the Fourier transform variables \((\mu,\nu)\) by \(x=\lambda f u\) and \(y=\lambda f v\), where \(f\) is the focal length of the eye, \(f=16.7\) mm, and \(\lambda\) is the wavelength, set to 550 nm as in the experiments [5]. The pupil function \( P \) is defined as

\[ P(\xi,\eta) = \begin{cases} \exp \left( \frac{2\pi i}{\lambda} W(\xi,\eta) \right) & \text{for } (\xi,\eta) \text{ in the aperture} \\ 0 & \text{elsewhere} \end{cases} \]  

(11)

\( W(\xi,\eta) \) is the wave aberration function, which was reconstructed from wavefront measurements obtained with a Shack–Hartmann wavefront sensor. The pupil sampling was 0.6 mm and the wavefronts were recovered using a Zernike modal reconstruction with 35 polynomials; the technique is detailed in [31]. The calculations were carried out with MATLAB, using fast Fourier transforms to compute the discrete Fourier transforms (DFT). We used a \( 1024 \times 1024 \) sampling resolution. The separability measure was computed with Eq. (7) based on the Euclidian magnitude difference between the image vectors.

3. COMPARISON OF THE MODEL-OBSERVER AND HUMAN-OBSERVER PERFORMANCE FOR ADAPTIVE-OPTICS-CORRECTED VISION

A. Validity of the Separability Measure

The interest of the separability measure given in Eq. (7) lies in the simplicity of its calculation. We mentioned already that it is proportional to the observer performance, as long as we assume a direct relation with the percentage of correctness in the human-observer experiment. For the purpose of this study we used the process model, and in particular Eq. (2), to test Eq. (9). The aim was the comparison between the ratio of the computed contrast thresholds (or contrast sensitivities) corresponding to a particular percentage of correct responses \( P \) (72% as set in the experiments) in two different conditions and the ratio of separability measure in the same conditions. Equation (2) is dependent on the noise variance \( \sigma^2 \), unknown and probably subject and light dependent. For two subjects of the study, and the two light levels implemented in the model, we varied the noise to match the computed percentage of correct responses to the measured percentage at the contrast threshold measured for a 6 mm pupil with the HO aberrations corrected. For each noise value the model-observer decision was computed for a run of 1000 realizations with random orientation and random noise and the percentage of correctness was derived from these calculations. Once the noise is evaluated, and because it can be considered equal without correction of HO aberrations, we computed the contrast threshold under that second condition. This calculation was based on a simulated 50 trials QUEST procedure [32] using the same parameters as those used in the experiments [5] and was repeated five times. The resulting ratio of contrast sensitivities with and without AO (inverse of the ratio of contrast thresholds), \( R_{cs} \), is compared to the ratio of the separability measure \( R_S \) in Table 1. The variability in the computed \( R_{cs} \) was defined as the standard deviation from the five QUEST runs. Although the ratio \( R_S \) is slightly above the ratio \( R_{cs} \) in the photopic regime it is

| \( \) Photopic \( \) Low Mesopic \( \) Photopic \( \) Low Mesopic | \( R_{cs} \) \( \) 1.82 ± 0.34 \( \) 1.63 ± 0.23 \( \) 1.91 ± 0.23 \( \) 1.70 ± 0.28 | \( R_S \) \( \) 2.00 \( \) 1.61 \( \) 2.09 \( \) 1.65 |
|---|---|---|---|

*Data obtained for subjects 5 and 7 [5] with a 6 mm pupil.*
well within the uncertainty; in the mesopic regime, the former is closer to the mean value of the latter. We will therefore assume the validity of Eq. (9) in the following and base our model- and human-observer comparison on the separability measure.

B. Comparison of the Model- and Human-Observer Adaptive Optics Benefit in the Photopic Regime

The separability measure $S$ that we use is in fact a metric that can be compared to other metrics derived in the field of retinal image quality [33]. The specificity of this particular metric is that it takes into account not only the optical and neural processing of the visual system, but also the visual task undertaken in the experiments (here, discrimination between four possible orientations of the stimulus). Following the same approach as that adopted in the literature when comparing metrics to experimental measurements of visual performance [34], we calculated the correlation between $S$ and the experimental contrast sensitivity. We used the measurements obtained in the photopic regime, with and without correction of HO aberrations, for the seven subjects and the different pupil sizes when applicable. These corresponded to 26 data points. In the calculations of $S$ we used the NTF corresponding to the photopic condition and the optical transfer function derived from the ocular wavefront measurements. The linear correlation coefficient between the two sets of data was 0.59. The performance of $S$ as a metric to predict contrast sensitivity for this particular test could be compared to many other metrics, but it is probably more relevant to choose another metric incorporating the NTF, such as the visual Strehl ratio computed in the frequency domain with the OTF (VSOTF), which was found by several authors to perform well with visual acuity tests [34,35]. We calculated the VSOTF as the volume under the OTF weighted by our photopic NTF, and found a correlation coefficient of 0.56 with the contrast sensitivity experimental data. These relatively modest values will be discussed in Section 4.

An advantage of the separability measure is that the ratio of $S$ with AO correction to $S$ without AO correction, defined as $R_S$ above, corresponds to the experimental AO benefit (ratio of the contrast sensitivity with AO correction to that without AO correction). It indicates, for a given light regime, the effect of the OTF (here due to HO aberrations only) on the observer visual performance. We computed the AO benefit for the experimental data mentioned above and compared the values to the measured AO benefits, as shown in Fig. 3. Also present in the figure are the results obtained when taking the ratio of the VSOTF with AO to that without AO, $R_{VSOTF}$. It can be noticed that while the AO benefit computed with $S$ compares well with the experimental data, the AO benefit computed with VSOTF is several times higher for all data points. This observation highlights the advantage of $S$ over VSOTF, as it gives an absolute estimation of the AO benefit. It should be noted that while the precision of the experimental values is represented in the graphs with the standard errors of the means of five measurements, it was more difficult to estimate the uncertainty on the numerical results. From some repetitive sample wavefront measurements carried out, the standard error was evaluated to be of the same magnitude of the experimental error, that is about 0.2 in the AO benefit.

To quantify the fit of the AO benefit provided by the ratio of the separability measures, we calculated the root-mean-square (RMS) error between the sets of points given in Fig. 3. As part of the study we also performed calculations including the Stiles–Crawford (SC) effect [36]. This effect can be modeled as an apodization in the pupil plane; effectively by using a Gaussian weighting function in the pupil function defined in Eq. (11). Since no individual data were available preliminary calculations were performed with a generic function found in the literature [36], $f(r)=10^{-0.05r^2}$. Table 2 shows the RMS error and the correlation coefficient between the experimental and computed AO benefit, for $S$ without SC effect, $S$ with SC effect, and VSOTF. The RMS error given by $R_{VSOTF}$ is much higher than that given by the separability measures. The correlation coefficients are more comparable, although the separability measure still perform better. It was found that the computations with $R_S$ (no SC) gave values slightly higher than the experimental data, such that with a least-square fit, the RMS error is the same as that for $R_S$ (SC) while the correlation coefficient is higher. The actual effect of the SC effect on the computations is probably not of significance since the effect on image quality is dependent on the position of the SC peak, which is highly subject dependent, and also due to the precision on each value.

![Graph showing measured and computed AO visual benefit in the photopic light regime for 13 sets of conditions (different subjects and pupil sizes).](image)

**Table 2. RMS Error and Correlation Coefficient Between the Computed and Measured AO Benefit**

<table>
<thead>
<tr>
<th>Metric</th>
<th>RMS error</th>
<th>$r$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_S$ (no SC)</td>
<td>0.22</td>
<td>0.83</td>
</tr>
<tr>
<td>$R_S$ (SC)</td>
<td>0.21</td>
<td>0.74</td>
</tr>
<tr>
<td>$R_{VSOTF}$</td>
<td>2.02</td>
<td>0.69</td>
</tr>
</tbody>
</table>
C. Effect of the Neural Transfer Function on the Model-Observer Adaptive Optics Benefit

The model- and human-observer performance was also compared in different light regimes. For the two subjects with whom the largest range of light levels was investigated (0.3/1 to 1000 Td), we computed the visual benefit given by the correction of HO aberrations using $R_S$ with the photopic and the low mesopic NTF curves. The absolute performance of $R_S$ to predict the AO benefit has already been discussed and we were interested here in the change of AO benefit with light level. Therefore, the difference between the logarithm of $R_S$ in the two light regimes was calculated and averaged over the two subjects. The results are presented in Table 3 and compared to the difference between the measured AO benefit for the two extreme light levels.

The negative computed change in the AO benefit with light level confirms the trend observed experimentally, that is a decrease of the AO benefit from the photopic regime to the low mesopic regime. It can be noted that the numerical values are lower than the experimental ones. Several factors can account for the discrepancy between the quantitative results, the first one being probably the approximation made for the representation of the NTF curves at different light levels. This issue will be commented on in Section 4.

The change of the NTF with light level therefore affects the influence of HO aberrations in the model-observer as well as the human-observer performance. It was noted earlier that this change is mostly characterized by a drop of the sensitivity as well as a shift of the peak frequency towards lower spatial frequencies as the light level is decreased. As an attempt to provide some intuitive explanation of the numerical results an analysis based on the spatial frequency characteristics of the visual task is given in Section 4.

4. DISCUSSION

Using the separability measure to assess the performance of the ideal observer we found good agreement between the computed and measured AO benefit and consistent results concerning the decrease of the AO benefit as the light level is decreased. We shall here discuss the possible sources of discrepancy between the model and human data and give some insight on the numerical results based on a spatial frequency analysis of the visual task.

Table 3. Computed and Measured Change in the AO Benefit from the Photopic to Lower Mesopic, Averaged Over Two Subjects (in Log Units)

<table>
<thead>
<tr>
<th>Pupil (mm)</th>
<th>6</th>
<th>5</th>
<th>4</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>-0.1</td>
<td>-0.08</td>
<td>-0.05</td>
<td>-0.02</td>
</tr>
<tr>
<td>Experimental</td>
<td>-0.16</td>
<td>-0.11</td>
<td>-0.08</td>
<td>-0.04</td>
</tr>
</tbody>
</table>

A. Numerical Correlation of the Model-Observer and Human-Observer Performance

We found modest correlation between the separability measure or the VSOTF and the experimental data concerning values of contrast sensitivity at the photopic light level. Higher correlation coefficients between metrics and experimental data have been reported in the literature [34]; however, it was found by Applegate et al., that the correlation for very good visual performance (20/17 or better visual acuity) is highly dependent on the testing conditions (luminance and contrast) [35]. It is therefore difficult to compare our data, obtained with a particular contrast acuity task, with previous reports in the literature. Furthermore, the contrast sensitivity data examined in this correlation study comes from different sets of experiments obtained in slightly different conditions, concerning the light level and the target presentation [5].

These parameters would certainly affect the visual performance data in terms of noise in the visual processes, hence it is questionable to pool all these data together for a correlation analysis. The small number of data points for a given condition prevents us from conducting a proper numerical correlation analysis, which is not the main objective of the paper.

The correlation was better between the computed and the measured AO benefit, in particular for the separability measure. It should be noted, however, that the number of data points was here reduced to 13. It was also shown that the separability measure, as compared to VSOTF, holds the advantage of providing an absolute estimation of the AO benefit when taken as a ratio (see the low RMS error in Table 2). To account for the RMS error we have already mentioned the uncertainty in the calculations due to the error in the aberrations measurement. It should be mentioned that measured ocular wavefronts show important variations due to ocular aberrations dynamics [37] and displacements of the subject’s pupil in front of the instrument (the measurement and correction of aberrations were performed over a fixed area) [38]. Furthermore, the sample wavefronts measurements were carried out either before or after the visual test, hence inducing more uncertainty, in particular for the measurements of corrected wavefronts. In addition, other possible sources of optical degradation (such as scattering) were neglected in the calculations. Finally, one could mention neural adaptation to ocular aberrations, a phenomenon still not well understood, but recently experimentally highlighted [39].

This may explain why the average computed visual benefit was higher than the experimental one. A hypothesis would be that the human observer is adapted to his own aberrations to a certain degree, such that his performance in the aberrated case is not as degraded by ocular aberrations as predicted. Alternatively, or in addition, it could be that in the corrected case the small amount of aberrations introduced (the correction of HO aberrations is never diffraction limited) is affecting his visual performance to a higher degree than predicted.

Concerning the discrepancy between the change with light level in the AO benefit computed with the separability measure, and the change experimentally measured, the main point is the validity of the NTF curves. We constructed two NTFs functions based on a particular set of
data found in the literature. The NTF was measured with interferometric techniques for two subjects and four light levels in the range of 300 to 0.3 Td [26]. The actual individual characterization of the NTF for each of our subjects at our light levels, using similar techniques, would certainly greatly benefit the model and is necessary for a rigorous quantitative analysis; this was beyond the scope of this work. Furthermore, an assumption that was implicitly used in this work was that the neural sampling (limited by photoreceptors or ganglion cells) would not affect the model. As will be discussed in Subsection 4.C, the spatial frequency content of the stimulus studied lies well below the sampling density of cones (120–160 cycles per degree [16]), which defines the photopic neural sampling frequency. However, in lower light regimes, as larger spatial summation occurs, aliasing phenomena may occur on some parts of the stimulus spectrum. An improvement of our model would be to take this aspect into account.

Finally, the numerical derivations are based on the relevance of the separability measure as a figure of merit of the observer visual performance in a multialternative discrimination task. He and Frey [40] recently argued that the Hotelling trace, which is a scaled version of our separability measure [see Eq. (5)] is not appropriate since it cannot distinguish the case where all alternatives are perfectly classified from that where two classes only are perfectly discriminated: Both cases yield an infinite Hotelling trace. We are not operating in these extremes ranges, so we will assume that it is a valid figure of merit.

B. Alternative Modeling Approaches

Alternative approaches are possible for the derivation of the model. In particular, as part of this study a different version of the model with channel templates was investigated. The use of a set of independent channel signals in detection tasks has been experimentally confirmed [41] and a channelized model observer has shown good agreement with human-observer performance in many different situations [27]. The Fourier transform of the retinal image (after optical filtering) was integrated independently over a set of 20 channels (five spatial frequencies and four orientations) to form an image vector \( \mathbf{s} \) from the channel outputs. The observation and decision stages were kept similar to those already described. Preliminary calculations were performed for a two-alternative forced-choice task (discrimination between two orthogonal directions) and compared to the results obtained with the overall neural filter model. The results showed that the channelized model is more sensitive to the optical filter, such that the computed AO visual benefit is higher than that computed with the overall filter model. The difference increases with the amount of ocular aberrations and the drop in visual benefit with the light level is more moderate. The channelized model could not be extended to the four-orientation problem due to issues in implementing phase discrimination in the model; no satisfactory solution was found. The unsatisfactory results and the longer computation time given by this preliminary investigation with the channelized model led us to dismiss it in favor of the overall filter model. Nevertheless, it would be of interest to further investigate channel templates and their role in such large spectrum discrimination tasks.

C. Analysis of the Stimulus Spatial Frequency Characteristics

The computations based on the separability measure confirmed the trend—experimentally observed—of the decrease of the AO benefit as the light level is decreased, for a contrast acuity discrimination task. An analytical study of the spatial frequency processing of the task can provide further explanation. With a similar aim, several authors have taken an approach based on the difference spectrum, that is, the difference between the Fourier spectra of the targets. Campbell and Robson first derived this analysis to explain how a sine-wave grating could be discriminated from a square-wave grating if the third harmonic in the square wave was at or above its own visual threshold [6]. More recently, Bondarko and Danilova calculated the difference spectrum of two orthogonal orientations of the Landolt C to identify the peak of the spatial frequency characteristics of the discrimination task [42]. Hess et al. later obtained crowding experimental data that confirmed the use of the difference spectrum peak by the human visual system [43]. However, the difference between the Fourier spectra of two targets does not take into account the phase difference. In our experimental study the four orientations included pairs of stimuli with similar magnitude but opposite phase. Therefore we followed the approach taken by Anderson and Thibos [44], who used the phase as well as the magnitude of the Fourier transform to calculate the difference spectrum (DS), with the aim of specifying how the different orientations of the target differ. We calculated the difference between the Fourier transforms of two possible orientations of our visual target and took the magnitude of the result to obtain the DS image. The radial average of the DS image provides a one-dimensional representation of the spectral content used by the observer to perform the discrimination between the two orientations. Figure 4 illustrates the calculation of the DS for two pairs of stimulus orientations.

In the context of our study, the interest of the DS lies in its filtering by the visual system in different conditions of optical aberrations and neural filtering. Figure 5 shows one 1D DS [from Fig. 4(b)] multiplied by the NTF in the photopic and low mesopic case, along with the MTF curves calculated for subject 5 before and after correction of HO aberrations with our AO system. The two filtered DS curves were normalized to their maximum. The ratio between the MTF after correction and the MTF before correction of HO aberrations indicates the ratio difference in contrast sensitivity for each frequency of the stimulus DS. As expected from the NTF curves in Fig. 2, the low mesopic filtered DS is more severely attenuated with spatial frequency than the photopic filtered DS. The initial DS from Fig. 4 is mostly in the medium range of spatial frequencies; with the low mesopic neural filtering, it is even more concentrated to lower spatial frequencies, where the difference between the corrected and aberrated MTF is smaller than at high spatial frequencies. This analysis agrees with the experimental and numerical results showing a decrease of the AO benefit as the light level is decreased from photopic to lower mesopic light level.

A study using filtered letters as stimuli for a contrast
sensitivity discrimination task has shown that the most pertinent frequency (i.e., the filter frequency providing the best observer performance) is approximately constant when expressed in cycles per degree for stimulus sizes ranging from 0 to 0.7 log MAR [8]. According to the authors, the optical and neural filtering could account for this observation, which agrees with our analysis. The relation between the peak of the spatial-frequency characteristics of letter identification and the CSF was demonstrated by Chung et al. [10], who compared experiments with bandpass filtered letters and model performance simulations based on the observer’s CSF measured at different eccentricities. In our study, the 1D DS peak is shifted towards lower spatial frequencies when the light level is changed from photopic to lower mesopic light level, and it could be interesting to confirm this analysis with experiments based on filtered stimuli. However, looking at the DS peak frequency can only give a partial understanding of the problem, since the observer probably uses more information to perform the task.

D. Extension to Other Stimuli

Finally, the study focused on a large spectrum visual stimulus to represent functional vision; however, it would be of great interest to extend it to other stimuli. For example, the role of the neural contrast sensitivity in the attenuation of the optical blur at low light level would be much less significant for narrow spectrum stimuli according to this model. Some preliminary experiments with Gabor stimuli, however, suggested a similar behavior with light level as that found with the Landolt C; we currently do not have an explanation for that. The authors plan to investigate a range of visual tasks in similar light levels in the hope to fully understand how optical and neural limitations interact in a normal range of environmental conditions. In particular, it would be interesting to conduct a similar experimental and theoretical study of visual acuity tasks, more widely used in a clinical environment.

5. CONCLUSION

We presented an analysis of the combined optical and neural effect on everyday visual performance based on a standard ideal-observer model for a multiclass functional visual task in different light regimes, partly customized to individual human data. When using a separability measure the model-observer performance was consistent with the human-observer performance, although quantitative comparison was limited due to the several approximations and sources of errors in the model. The numerical results showed good agreement with experimental data in the assessment of the effect of the optical transfer
function (corresponding to a correction of higher-order aberrations) on visual performance in the photopic light level and supported the experimental finding that at low light level the neural contrast sensitivity moderates the effect of optical blur on visual performance. The model was applied to a specific visual task and obviously requires further validation with other visual tests. It could also be improved with further individual data. It is hoped that this analysis can provide a better understanding of the observer performance for everyday functional vision.

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