Introduction

In transparency perception the visual system assigns transmission-related attributes to transparent layers. Based on a filter model of perceptual transparency we investigate to what extent these attributes remain constant across changes of background and illumination. On a computational level, we used computer simulations to test how constant the parameters of the filter model remain under realistic changes in background reflectances and illumination and found almost complete constancy. This contrasts with systematic deviations from constancy found in cross-context matches of transparent filters. We show that these deviations are of a very regular nature and can be understood as a compromise between a proximal match of the mean stimulus color and complete constancy as predicted by the filter model.

Keywords: color perception, perceptual transparency, perceptual constancy, object recognition

colored background, whereas the background of the adjustable filter was always achromatic. In the majority of cases observers were able to make close to veridical matches. However, there were also some cases in which the settings deviated systematically from veridicality, especially if background and filter spectra had little overlap. Khang and Zaidi (2002b) focused more on the functional aspect of object identification than on appearance. They simulated natural illuminants, materials, and filters and used a forced-choice procedure to simultaneously measure thresholds for identifying filters across illuminants and discrimination thresholds within illuminants. The main finding was that if observers could discriminate between two filters within illuminants, they could also identify them across illuminants.

These previous studies are all limited in some way or the other. An obvious limitation is to consider only achromatic scenes. Another one is the focus on changes in background without a thorough consideration of confounding illumination effects. In the investigations referring to filter transparency an explicit psychophysical model is missing, which makes it difficult to relate the findings to perceptual processes. Some of the findings also seem to be mutually inconsistent, for instance those of Gerbino et al. (1990) and Robilotto and Zaidi (2004). Furthermore, Kingdom (2011) points to limitations in the matching protocols used in these studies, which restrict the subjects’ settings to one of the two or more dimensions that determine perceived transparency and may in that way prevent that the best possible match can be achieved.

The aim of the present research was to investigate to what extent perceptual attributes of transparent layers remain constant under two kinds of context changes, namely changes in the background seen through the transparent object and changes in the prevailing illumination. Our investigation is based on the filter approach to perceptual transparency discussed in Faul and Ekroll (2011) that considers transparency perception as the result of an attempt of the visual system to recognize and discriminate optical filters. In particular, we focus on the filter model proposed in Faul and Ekroll (2002) that putatively describes a color-related cue to transparency. In order to avoid the methodological problems highlighted by Kingdom (2011), we always gave the subjects in our matching experiments control over the complete parameter space that—according to this model—determines the perceived properties of the transparent layer. In the achromatic domain a similar strategy has previously been pursued by Gurnsey, Kingdom, and Schofield (2007).

In the section called The filter model of perceptual transparency, we briefly recapitulate some relevant properties of this model. In the section called Constancy from a computational perspective, we investigate transparent layer constancy at the model level. On this level, complete constancy would hold if the model parameters estimated from inputs caused by a fixed distal filter object remain constant under varying context conditions. The results of computer simulations indicate that a high degree of constancy can be expected under realistic variations in background reflectances and illumination. In the section called Measuring constancy using asymmetric matching, we describe six closely related psychophysical experiments in which subjects were asked to match the perceived properties of a fixed filter given in one context by adjusting the parameters of a comparison filter presented in a second context. Systematic deviations from constancy were found in these phenomenal tests. A close inspection of these deviations suggests that they can be understood as a compromise between a proximal match and a match based on complete constancy, that is, as a “regression to the real object” (Thouless, 1931). We show that a simple model constructed along this idea allows describing the subjects’ settings to a good approximation.

### The filter model of perceptual transparency

We interpret the filter model proposed in Faul and Ekroll (2002) as a formal description of a color-related cue to transparency that contributes—along with additional cues exploiting other input regularities—to an internal representation of transparent objects and their properties.

This interpretation of the model is supported by empirical findings showing (a) that it describes changes in background colors caused by optical filters to a good approximation, (b) that its parameters can be computed from the retinal input in an unique way, (c) that it successfully predicts perceived transparency, and (d) that the model parameters stand (after a suitable transform) in a close relationship to dimensions of phenomenal transparency impressions (Faul & Ekroll, 2002, 2011).

In this section we summarize some properties of the filter model reported in our previous papers (Faul & Ekroll, 2002, 2011) that are of direct relevance for our investigation of transparent layer constancy.

### General assumptions

The model makes a number of simplifying assumptions about the scene and the viewing conditions: (a) All spectra are smooth and relatively broadband, (b) the illumination is diffuse and spatially uniform, (c) the filter is flat and of constant thickness, (d) filter and
background are coplanar, and (e) the viewing direction is perpendicular to the filter surface.

With the exception of assumption (a), which presumably reflects true natural regularities, these assumptions basically ensure that the resulting images are similar to the flat, mosaic-like stimuli traditionally used in investigations of transparency (D’Zmura et al., 1997; Kasrai & Kingdom, 2001; Metelli, 1974, 1985; Singh & Anderson, 2002).

### Image generation model

Under these simplifying assumptions, the image generation model for optical filters without scattering is relatively simple and can be given in closed form. In the following, we briefly summarize these well-known results (a more detailed account can be found in Faul & Ekroll, 2002; Nakauchi, Silfsten, Parkkinen, & Usui, 1999; Robilotto, Khang, & Zaidi, 2002).

The three parameters of the optical filter are the absorption spectrum \( m(\lambda) \), \( 0 \leq m(\lambda) \leq 1 \), the filter thickness \( x \geq 0 \), and the refractive index \( n \). The Bouguer-Beer law \( I_1/I_0 = \theta(\lambda) = \exp[-m(\lambda)x] \) describes how the inner transmittance \( \theta(\lambda) \) (the ratio of the amount \( I_1 \) of light reaching the bottom of the filter to the amount \( I_0 \) entering at the top) depends on absorption and thickness. Fresnel’s equations describe how the relative amount \( k \) of light that is specularly reflected at each air-filter interface depends on the angle of the incoming light and the refractive index. For normal incidence as assumed here, \( k = (n-1)^2/(n+1)^2 \).

For a flat filter of constant thickness and normal incidence of light, the total reflection \( r(\lambda) \) and total transmittance \( t(\lambda) \) (i.e., the relative amounts of light leaving the filter after multiple inner reflections at the illuminated side and the opposite side, respectively) can be given in closed form: \( r(\lambda) = k + k(1-k)^2\theta^2(\lambda)[1-k^2\theta^2(\lambda)] \), and \( t(\lambda) = (1-k)^2\theta(\lambda)[1-k^2\theta^2(\lambda)] \). If the filter is placed in front of a background with reflectance \( a(\lambda) \), then the virtual reflectance \( p(\lambda) \) of the filter surface (i.e., the relative amount of incident light that is reflected from the filter area) can be written as:

\[
p(\lambda) = \frac{r^2(\lambda)a(\lambda)}{1 - r(\lambda)a(\lambda)} + r(\lambda).
\]

Given \( p(\lambda) \), the cone excitation \( P_i \), \( i = L, M, S \) can be computed in the usual way, that is, \( P_i = \int \lambda p(\lambda)I(\lambda)R(\lambda) \, d\lambda \), where \( I(\lambda) \) is the illumination spectrum and \( R(\lambda) \) the sensitivity spectrum of cone class \( i \).

### Psychophysical model

The color changes in background colors caused by optical filters can be well described by a simple model formulated in terms of color codes (Faul & Ekroll, 2002). The predictions of this psychophysical filter model for a situation with two background regions are given by

\[
P_i = \tau_i(A_i + \delta I_i) + \mu \delta I_i,
\]

\[
Q_i = \tau_i(B_i + \delta I_i) + \mu \delta I_i,
\]

where \( A \) and \( B \) denote the color codes of the bipartite background region and \( P \) and \( Q \) the color codes of the same regions viewed through the filter (see equations 17 and 18 in Faul & Ekroll, 2002). In the following we will always assume that the color codes are cone excitations where the index indicates one of \( L, M, \) or \( S \).

The four colors \( A, B, P, \) and \( Q \) describe the input from which the other model parameters \( I, \tau, \) and \( \delta \) must be inferred. \( I \) is the color of the illumination. A comparison of the model equations with a simplified version of the image generation model suggests (see Faul & Ekroll, 2002, p. 1086) that the vector \( \tau \) is related to the squared total transmittance \( \tau^2(\lambda) \) and that \( \delta \) is related to the direct reflection factor \( k \). This motivates the parameter restrictions \( 0 \leq \tau_i \leq 1 \), and \( \delta \geq 0 \).

The remaining parameter \( \mu \) controls the relative amount of directly reflected light of first order that is reflected from the top surface of the filter to higher order contributions that traveled through the filter and are thus affected by its transmissive properties. Here it mainly has a technical meaning and is used to distinguish between a “full” model with \( \mu = 1 \) and a “reduced” model with \( \mu = 0 \), which we considered in Faul and Ekroll (2002, 2011).

The model in Equations 2 and 3 does not specify how the illumination \( I \) is determined from the input. But whatever method is used, it follows from Equations 2 and 3 that

\[
\tau_i = \frac{P_i - Q_i}{A_i - B_i},
\]

which shows that the transmittance factors \( \tau_i \) do not depend on the illumination. The computation of the factor \( \delta \), in contrast, requires knowledge about the illumination:

\[
\delta = \frac{A_iQ_i - B_iP_i}{(A_i - B_i + P_i - Q_i)I_i}.
\]

In the following, we will assume that \( \mu = 0 \) and that the illumination color is determined from the mean of the background colors within a framework, that is, a region of common illumination in the proximal stimulus (for the framework concept, see Gilchrist et al., 1999). As will be shown below, the latter would be a reliable strategy if the gray-world assumption (Buchsbaum, 1980; Land, 1977) is approximately true.
Parameter estimation

In Faul and Ekroll (2011) we proposed robust estimation techniques for the model parameters that use the mean and standard deviation in sets of two or more related background $A$ and filter colors $P$. They use the following equations:

$$\tau_i = \frac{\text{sd}(P_i)}{\text{sd}(A_i)},$$  
$$\delta = \frac{\text{mean}(P_i) - \tau_i \text{mean}(A_i)}{(\tau_i + \mu)I_i},$$

where the index $i$ refers to color channel $i$. In this previous work we also showed how problems with singularities $[\text{sd}(A_i) = 0$ in some channels $i]$ can be avoided and discussed pros and cons of this approach.

Alternative parameterization of the filter model

In Faul and Ekroll (2011) we also proposed an alternative parameterization of the filter model. The parameter vector $\tau$, which in the original model was interpreted as channel-wise transmittance, is transformed to the alternative filter parameters “hue” ($H$), “saturation” ($S$), and “overall transmittance” ($V$), whereas the parameter $\delta$, which in the original model represents the amount of direct reflection, is transformed to a bounded “clarity” parameter ($C$).

The names given to these alternative parameters are motivated by the changes in perceived properties of transparent filters observable under isolated variation of these parameters (see Figure 1 for an illustration). Under the assumption that phenomenal impressions partly reflect properties of activated internal representations, we may conclude that these parameters are more closely related to dimensions of the internal representation of transparent objects than the original parameters, which emphasize the relation to image generation. Note, however, that these two parameter sets are completely equivalent with respect to the underlying model and can be uniquely transformed into each other.

Constancy from a computational perspective

An important step in validating a potential visual cue is to check how well it supports the detection of target objects and their properties. As already noted, the filter model is thought to describe a color-related cue to transparency, where the parameter values estimated from the input correspond to the cue’s response. An important criterion for the presence of a target object is that these parameters remain within certain critical bounds. If this is the case, then the specific parameter values describe subjectively relevant properties of the detected target object. This interpretation is supported by our previous finding (Faul & Ekroll, 2002) that the color relations generated by an arbitrary optical filter in an arbitrary scene (of the restricted type assumed in the model) can always be well fitted by setting the parameters of the filter model to suitable values within admissible bounds.

In this section, we investigate a further essential property expected from a useful and reliable cue, namely that its response to a fixed target object remains approximately constant under ubiquitous changes in viewing conditions. We describe computer simulations that were used to determine the degree of constancy exhibited by the filter model. The core procedure was to simulate the input for a fixed target object (i.e., an arbitrary optical filter) in an arbitrary scene (of the restricted type assumed in the model) can always be well fitted by setting the parameters of the filter model to suitable values within admissible bounds.

In this section, we investigate a further essential property expected from a useful and reliable cue, namely that its response to a fixed target object remains approximately constant under ubiquitous changes in viewing conditions. We describe computer simulations that were used to determine the degree of constancy exhibited by the filter model. The core procedure was to simulate the input for a fixed target object (i.e., a certain optical filter) under variations in context and to measure the fluctuations in the parameters of the filter model estimated from the corresponding input. The degree of constancy found in this way puts an upper bound on the degree of constancy that may be observed.
in transparency perception, if the visual system would solely rely on this single cue.

In the simplified situation assumed in the model, the central physical parameters of optical filter are the absorption spectrum $m(\lambda)$, the refractive index $r$, and the thickness $t$, whereas the context is given by the spectrum of the illuminant and the reflectance spectra of the background colors. To get a realistic picture of the degree of constancy to expect under natural viewing conditions, we drew representative samples from all these physical values.

**General method**

The logic of the simulation study is illustrated in Figure 2. The image generation model given in Equation 1 was used to simulate the input into the visual system that is produced by a fixed optical filter under different choices of background and illumination. For each simulated input, the parameters $\tau$ and $\delta$ of the filter model were estimated by applying one of the robust estimation procedures (Case 3, $f_L$) proposed in Faul and Ekroll (2011, p. 6f). From these values, the alternative parameters $H$, $S$, $V$, and $C$ were also computed. The variance of the estimated parameter values across contexts was then used as a measure of constancy, with zero variance indicating complete constancy. An important variable that influences estimation accuracy is the number $N$ of background and filter color pairs that enter into the estimation procedure. We therefore also considered the degree of constancy as a function of $N$. In all simulations reported below, the absorption spectra of the filter and the reflectance spectra of the backgrounds were randomly generated frequency limited spectra (see Faul & Ekroll, 2011; Wyszecki & Stiles, 1982) with limiting frequencies of $1/150$ cycles/nm and $1/75$ cycles/nm, respectively. The absorption spectra were rescaled to the range $[0.1, 0.8]$ to introduce a bias for highly saturated filter colors, and the reflectance spectra were multiplied with a random factor between 0.1 and 1 to increase the variance in albedo. All spectra were sampled from 400 to 700 nm in steps of 5 nm.

**Accuracy of the illumination estimation**

The chromaticity of the illumination must be known in order to be able to estimate the direct reflection parameter $\delta$ (or, in the alternative parameterization, the clarity of the filter). A simple assumption often made in our earlier papers is that the arithmetic mean of the background colors is used to estimate the illumination color. To investigate the accuracy of this estimate, we computed $2 \leq N \leq 20$ background colors resulting from randomly generated reflectance spectra under a certain illuminant. It was then determined how far the chromaticity of the mean of $N$ background colors $\hat{x}$ deviated from the expected chromaticity $x$ that was directly computed from the spectrum of the illuminant. All computations were done in the CIE UCS 1976 ($u'$, $v'$)-chromaticity space (Wyszecki & Stiles, 1982, p.165).
Results

Figure 3 shows the distribution of the error $\Delta x = \hat{x} - x$ in samples of 500 estimates. The illuminations were daylight spectra of different temperature, ranging from reddish (3000 K) over neutral (6500 K) to blueish (30,000 K). The distributions appeared unbiased, that is, roughly centered at zero. The two left panels illustrate the distribution for two special cases in detail and the right panel summarizes the complete results. The latter shows that the error measure (length of the major semi-axis of the $2\sigma$ error ellipse) shrinks rapidly with $N$ and flattens out at approximately $N = 10$ at a value of less than 0.01. Expressed in $\Delta E_{ab}$ the mean deviation approaches a value of approximately 6. This is clearly above detection threshold, which was found by Stokes, Fairchild, and Berns (1992) to be approximately 2.3 in successive image comparisons, but nevertheless a rather small and hardly noticeable value.

These results suggest that random choices of realistic reflectance spectra provide rather reliable estimates of the illumination color even if only a relatively small number of surface regions are present in the background.

Constancy under background changes

To investigate the question of how constant the estimates of the filter parameter remain under changes in background colors, we used a method comprising the following three steps (see Figure 2 for an illustration): (a) Compute the input into the visual system for a fixed optical filter, a fixed illumination, and $n$ randomly chosen background patterns, (b) estimate the parameters of the filter model for each of the $n$ input patterns, and (c) compute the standard deviation of the individual estimates. Complete scene constancy would hold if the estimates were identical for different backgrounds, which implies a standard deviation of zero. The standard deviation is here used as a measure of constancy, because the true value of these perceptual variables is not known.

A set of 180 filters was used, in which 20 randomly generated absorption spectra were combined with three thickness values $t$ (0.5, 1, 1.5) and three refractive indexes $r$ (1 = no refraction, 1.3 = refraction of water, 1.6 = refraction of glass). The backgrounds consisted of $N = 2$ to $N = 10$ regions, and the color of each region was determined from a frequency limited reflectance spectrum that was randomly selected from a set of 200 precomputed spectra. For each $N$, $n = 50$ random backgrounds were generated. The spectra of the 50 illuminants were randomly generated frequency limited spectra ($\omega = 1/75$ cycles/nm) that were normalized to have the same luminance. Thus, in total, $180 \times 9 \times 50 \times 50 = 4,050,000$ stimuli were computed. Figure 4 illustrates the range of illuminations, reflectances, and transmittances used in the simulations.

Results

The evaluation of the degree of constancy in parameter estimates is complicated by the fact that the metric of the corresponding subjective scales is not known. The same nominal hue difference, for instance, may appear very different in size, depending on where it is located along the hue scale. Thus, using standard deviations on nominal parameter values may lead to a somewhat distorted picture. To alleviate this problem with respect to the transmittance parameter $\tau$ and its alternative representation in terms of hue $H$, saturation
S, and overall transmittance \( V \), we not only determined the standard deviation of the estimates of \( H \), \( S \), and \( V \) but also applied \( \tau \) estimates to a nominally white background color \( W \); that is, we computed \( W = \tau W \) and determined the standard deviation of the resulting color codes in a uniform color space (CIE UCS, 1976). The nominal range of the \( H \), \( S \), \( V \), and \( C \) parameters is the interval \([0, 1]\) and a standard deviation of 0.1 of parameter estimates may thus be interpreted as an error of about 10 percent. It should be kept in mind, however, that the hue scale is perceptually nonuniform, that the range of saturation values for a given hue is often restricted to values smaller than one, and that the clarity scale starts at values greater than zero (see Faul & Ekroll, 2011).

Figure 5 shows example results for a filter thickness of \( t = 1 \) and a refractive index of \( r = 1.3 \) in detail. The first and second columns show the distribution of the deviation of \( W \) around the mean estimate in the chromaticity space and the corresponding 2\( \sigma \)-error ellipse. The scatter plots shown in the second column enable one to see the total range of values found in the simulation, whereas the contour plot of the 2D histograms shown in the first column is better suited for judging the form of the distribution. The contour lines in the latter plots mark 1/11 to 10/11 of the histogram height and the 1/11 height contour is very close to the error ellipse. Figure 6 shows, in a more condensed form, how the variability of the parameter estimates depends on the thickness and the refractive index of the simulated optical filter. The results indicate a slight increase in variability with increasing values in both the thickness and the refractive index. The left panel in Figure 7 shows that the variability of the parameter estimates decreases rapidly with increasing numbers \( N \) of background regions used in the estimation procedure.

### Constancy under illumination changes

To investigate the degree of constancy under illumination changes, a similar method as in the previous section was used. Here, the corresponding three steps were (see Figure 2 for an illustration): (a) Compute the input into the visual system for a fixed filter, a fixed background, and \( n \) different illuminations, (b) estimate the parameters of the filter model for each input, and (c) compute the standard deviation of the parameter estimates. Complete constancy under illumination changes holds if this deviation is zero. All conditions realized in the simulation were identical to those used in the previous section.

### Results

Figure 8 shows the degree of constancy observed under illumination changes depending on the filter thickness and the refractive index. These plots have the same condensed format as those shown in Figure 6 and refer to distributions with the same format as those shown in Figure 5. Again, each data point is based on 50,000 estimates (20 Absorption Spectra \( \times \) 50 Backgrounds \( \times \) 50 Repetitions). The variability in most parameters increases with increasing values in both the thickness and the refractive index. The right panel in Figure 7 shows how the parameter variability depends...
Figure 5. Variability of parameter estimates under changes in background reflectance. The top and bottom row show the data for estimates based on $N = 2$ and $N = 10$ color pairs, respectively. The results in each panel are based on 50,000 estimates (20 Absorption Spectra $\times$ 50 Illuminations $\times$ 50 Repetitions). The first three columns from the left refer to the CIE 1976 $uvL$ coordinates of a nominally white background color (EE-white) that has been multiplied with estimates of the transmittance parameter $\tau$. The leftmost panels show the distribution of the $uv$-coordinates around the mean $uv$-estimate. The $i$th contour line corresponds to $i \times 10\%$ of the height of the smoothed frequency histogram. The dashed red line shows the error ellipse corresponding to a SD of 2$\sigma$. The diagrams in the second column show corresponding scatter plots (note the difference in axis scale). The plots in the third column show the histogram of $dL/L$, where $dL$ denotes the deviation of the luminance from the mean luminance estimate $L$. The red curve shows the fit of a $t$ location scale distribution to the histogram. The scale parameter of this fit is used as an estimate of the standard deviation of the distribution. The rightmost panels show the SD of the hue ($H$), saturation ($S$), transmittance ($V$), and clarity ($C$) parameters.

Figure 6. Variability of filter parameter estimates under changes of background colors depending on the refractive index $r$ and filter thickness $t$. Backgrounds with $N = 10$ regions were used throughout. The values lying on the dashed line in the middle panel correspond to those shown in detail in the lower row of Figure 5.
on the number $N$ of background regions used in the estimation procedure.

**Discussion**

Our first result indicates that rather accurate estimates of the illumination color can be obtained by taking the mean over small sets of surface colors, provided that the reflectances are randomly selected from a set of realistic (i.e., smooth and broadband) spectra. The assumption of a random selection of reflectances is not very realistic, but a possible increase in estimation error by nonrandom selection is somewhat counteracted by the fact that most surfaces in natural environments are less colorful than those used in the simulation. This suggests that the simulation results are at least in the right ballpark.

The results about the variation in parameter estimates under changes in background show almost perfect constancy for low filter thickness $t$ and a refractive index $r$ of 1. The variability of the estimates increases (but is still low) for larger values of $r$ and $t$. Increasing $r$ leads to an increase in the amount of direct reflection at the top surface of the filter, which solely depends on the illumination. Thus, inaccuracies in the illumination estimation increasingly add to the variability of the estimated filter properties, especially that of the clarity parameter. The observed effects of changes in filter thickness $t$ can be understood from...
the fact that the hue and the saturation parameter depend only on the ratio of the mean color in the background and the mean color in the filter region of the stimulus (see Faul & Ekroll, 2011, figure 3). For very thin filters (i.e., high transmittance values) these two means are (whatever the background colors) very similar and thus lead to almost identical estimates. With thicker filters, the two means get increasingly different and thus inaccuracies of the model in describing the color changes caused by optical filters have a more pronounced influence on estimates of the hue and saturation parameter. This analysis suggests that the variability of the parameter estimates under changes in background reflectance depends mainly on the variability of the mean color in the background and the filter region of the stimulus. This also explains why the constancy rapidly increases with increasing numbers of background colors.

The results about the variation in parameter estimates under illumination changes also indicate high constancy in most cases. The effect of changes in $t$ and especially in $r$ are here less pronounced. If the model describes the changes in background colors caused by optical filters perfectly, then according to Equation 4 changes in illumination would have no effect on the transmittance parameter $\tau$ and the alternative parameters $H$, $S$, and $V$. The increase in parameter variability with increasing thickness thus indicates that the accuracy of the model prediction is worse for thicker filters. This is plausible, because due to the exponential decrease in transmittance with filter thickness the transmittance spectrum does not only have a smaller maximum but gets also increasingly more wavelength selective (spectral sharpening) and is therefore more susceptible to changes in the illumination spectrum. This effect is especially pronounced for the highly saturated (i.e., highly wavelength-selective) filters used in the simulation. These errors are more of a systematic nature and do not decrease with increases in the number of background regions.

In summary, we may conclude that the filter model does not only accurately describe the color changes caused by optical filters, but that the estimated parameters that putatively represent internal properties of transparent objects remain remarkably constant under changes in background and illumination. The color relations captured by the filter model therefore seem well suited to contribute as a cue to transparency.

Measuring constancy using asymmetric matching

The results of the simulation study suggest that the parameters of the filter model characterize relevant properties of light transmitting objects in a way that is rather robust against changes in context. If the visual system actually uses the input relations captured in the filter model as a cue for transparency perception, then the systems behavior should reflect a similar degree of constancy. To investigate this, we explored to what extent the properties of a perceived transparent layer remain constant under variations in surface reflectance (scene constancy) and illumination (illumination constancy) in six experiments.
Experiments

In each experiment, the task of the subjects was to match the appearance of two filters presented in different contexts by interactively adjusting the parameters of one of them. In the simple scenes used in the experiments, reflectance and/or illumination changes across scenes manifest themselves in characteristic patterns of changes in background colors (see Figure 10). Figure 9 illustrates the four types of background changes used in the experiments. As explained in more detail below, the colors in each of these backgrounds were computed from simulated frequency limited reflectance spectra under different daylight illuminations.

Experiment 1 was a control experiment with identical backgrounds (Figure 9, left). In this case no constancy (and not even a transparency impression) is necessary to achieve a perfect match. The main purpose of this experiment was to test the usefulness of the adjustment procedure and its accuracy and precision under ideal matching conditions. In Experiment 2 backgrounds with different reflectances but the same illumination were used (Figure 9, second from left) to perform an isolated test of scene constancy. In Experiment 3 an isolated test of illumination constancy was performed with background colors that were computed from the same reflectances but different illuminations (Figure 9, third from left). In Experiment 4 the backgrounds differed both in reflectance and illumination (Figure 9, right).

In Experiments 1–4, the standard and comparison stimuli were presented side by side. From a theoretical perspective this should be unproblematic if the simulated illumination is identical in both stimuli (as in Experiments 1 and 2), but in cases where the simulated illumination differs (as in Experiments 3 and 4) it is possible that this influences the interpretation of the stimulus. Therefore, two additional experiments were performed that replicated the conditions realized in Experiments 3 and 4 under an alternating presentation of standard and match stimulus. In the following we will use the labels CON, SC, IC, SIC, IC_A, and SIC_A to refer to Experiments 1–6, where the first four correspond from left to right to the conditions shown in Figure 9 and the suffix “_A” denotes alternating presentation mode.

Methods

The standard and comparison stimuli were presented stereoscopically one above each other on a calibrated CRT-Monitor (ViewSonic P227f, 21 in, 1280 × 980 pixel, 75 Hz refresh rate, controlled by a graphics card NVidia 8600GT with a bit-depth of 8 bits). The stereoscopic viewing was chosen to support a holistic viewing mode and to enhance the depth stratification that usually accompanies transparency impressions. The subjects viewed the stereo pairs from a distance of 80 cm through a mirror stereoscope (SA200 ScreenScope Pro).

Figure 10 shows a screen shot of the central part of a display in the simultaneous presentation mode used in Experiments 1–4. The display in the alternating presentation mode used in Experiments 5 and 6 was exactly the same except that the standard and comparison stimulus were displayed in alternation for 1 s each. The uniform area outside the stimuli was always set to the mean of the background colors in the displayed stimuli. In simultaneous presentation mode this was a fixed color corresponding to the mean across standard and comparison backgrounds. In alternating presentation mode it was based on the currently presented stimulus and thus changed between the mean of the standard background and the mean of the comparison background. The square background area of the stimuli had a side length of 8.7 cm (6.2") and the diameter of the circular filter region was 5 cm (3.6`). The horizontal center to center distance of the background rectangles was 10.5 cm (7.5`) and that of the circular filter regions 9.5 cm (6.8`).

Three CIE daylight illuminants with a color temperature of 4000 K (reddish), 6500 K (neutral), and 20,000
they had to press the response keys without visual subjects' view was restricted by the mirror stereoscope and the filter in the standard stimulus with a second filter and the experiment. In each display the subjects had to match the filter in the standard stimulus with a second filter in the comparison stimulus by adjusting the $H$, $S$, $V$, and $C$ parameters of the filter model. Since the subjects' view was restricted by the mirror stereoscope they had to press the response keys without visual control. To facilitate this, we restricted the number of keys to the four arrow keys (to change the values of either $H$ and $S$ or $V$ and $C$ up and down), the space key to switch between both input modes, and the return key. Feedback on the currently active input mode was given on screen. The starting value for the $V$ parameter was always chosen to be 0.75 (the expected value under complete constancy), whereas all other parameters were given random values within their admissible range. The subjects were instructed to first try to match the filter by only adjusting $H$, $S$, and $C$ and to use the adjustment of $V$ only as a last resort. This instruction was given because, in the simple stimuli used in the experiment, there are cases where the perceptual effect of a change in $C$ can partly be compensated by a change in $V$, and vice versa. A decrease in $C$, for instance, which increases the contribution of the additive term (direct reflection) and thus the overall brightness in the filter region, can partly be compensated by a decrease in $V$, which leads to a lower overall transmittance. Focusing on $C$ first helps to avoid possible confusions during the setting procedure, but may lead to distortions in the balance of $V$ and $C$ in the aforementioned cases.

Only one parameter could be changed at a given time and the change was immediately reflected on screen by recomputing the model prediction under the new setting. An acoustic feedback was given if the subjects ran into a boundary of the admissible range of the manipulated parameter. There was no time limitation for the setting. After the subjects had the impression that they found the best possible match, they pressed the return key and then rated the quality of the match on a scale from zero (no match possible) to five (perfect match). Before the start of the first experiment each subject conducted a few training settings using the display of the control condition in which a perfect match is always possible. This was done to make the subjects aware of possible pitfalls in the setting procedure: A first one is that changes in the hue parameter $H$ are only noticeable for saturations $H > 0$ and a second one that lowering the clarity parameter $C$ decreases the maximally possible value for $S$. Due to the latter restriction it may be necessary to first decrease $S$ to a lower value in order to be able to reduce the value of $C$.

Nine standard filters were used, which varied in three steps in the hue ($H = 0.2, 0.64, 0.98$) and clarity ($C = 0.5, 0.75, 1$) parameters. The transmittance parameter was always set to $V = 0.75$ and the saturation was set to 35% of the maximally possible saturation at the chosen hue on a background with gray mean (see Figure 11). The filtered colors in the standard stimulus were computed by applying the filter model with the chosen parameters to the background colors. We repeated this procedure if necessary until all colors in the standard stimulus and the colors in the comparison stimulus predicted by the model under the assumption of complete constancy were realizable on the CRT monitor used in the experiment.

In this way, 27 displays ($3$ Filter Hues $\times 3$ Filter Clarities $\times 3$ Illuminants) were generated for each experiment. In each display the subjects had to match the filter in the standard stimulus with a second filter in the comparison stimulus by adjusting the $H$, $S$, $V$, and $C$ parameters of the filter model. Since the subjects' view was restricted by the mirror stereoscope they had to press the response keys without visual

![Figure 11. The nine standard filters used in the experiments. They vary in three clarity steps and three hue steps. See text for details.](image)

K (blueish) were used. The background was always a square with 10 subregions and their colors were computed in the following way: First, 10 frequency limited spectra with a limiting frequency of $\omega = 1/100$ cycles/nm were randomly generated and afterwards multiplied with a random factor between 0.275 and 0.725 to increase the range in albedo. After applying one of the illuminants, the cone excitations were computed and slightly adjusted (by shifting all color coordinates by a color vector) to guarantee that the mean chromaticity was exactly identical to that of the illuminant. Finally, all colors were scaled such that the mean of (L + M) was 12 (which corresponds roughly to a luminance of 12 cd/m²).

Scientific members of staff and experienced visual observers. The order of experiments was CON, SC, SIC, SIC_A, IC, and IC_A. One of the subjects performed all experiments twice, and two other subjects participated only in the first four experiments. Each of the experiments was completed in one session of 1–2 hours, and each subject performed the whole series of experiments on different days within three weeks.
Results

The subjects’ settings were very similar both within and across subjects and we therefore only report mean data in the following. Figure 12 shows the subjects’ mean ratings of the match quality for all six experiments. They were high throughout with a total mean of 4.2. This finding is in line with the subjects’ informal reports that they did not have had any serious problems in finding a satisfactory match. It also indicates that the restrictions imposed by the filter model on the settings had no detrimental effect on the quality of the match.

Figure 13 shows, for each experiment, how far the subjects’ filter parameter settings deviate from those used in the standard stimulus. The error in the $V$ parameter is very small and of comparable size in all experiments. Actually, adjustment of the $V$ coordinate was almost never needed to achieve a match and in the rare cases where the starting value of $V = 0.75$ was changed at all, it was adjusted only very slightly. We may therefore conclude that the context changes used in the experiment have almost no effect on perceived transmittance (but see the remarks at the end of the next section). This result is in line with the findings of Gerbino et al. (1990) in the achromatic domain.

The size of the errors in the $C$ parameter are also rather similar across experiments. That the errors in the control condition and about 1/3 of the difference between two consecutive clarity steps realized in the experiment (see Figure 11). A closer inspection of the deviations for $C = 0.5$ and $C = 0.75$ revealed an almost symmetric distribution of the settings around the predicted value. This suggests that the observed deviations are best interpreted as random errors. We may thus conclude that the subjects were, in general, well able to isolate and match the clarity aspect of the filters across different contexts. To test for possible erroneous compensations of mismatches in $V$ by adjusting $C$ that may result from the instruction to first adjust $C$ (see methods section), we visually checked the transmittance part of the mean matches in isolation, that is we set always $C = 1$ in standard and match instead of the actual values. In these partial matches a potential crosstalk between the $C$ and $V$ parameters would manifest itself in a noticeable mismatch between the overall transmittance in the standard and the filter match. There were indeed such cases, especially in the $C = 0.5$ condition, and the mean relative adjustment of $V$ needed to reestablish a match was approximately 8%. Thus, parts of the errors found in the settings of the $C$ parameter can be attributed to this problem.

A clearly different pattern emerges in the plots of the $H$ and $S$ parameters. Here, the error is small in both the CON and SC conditions, but huge in comparison in all
Figure 14. Predicted and observed settings for the transmittance parameter across different illuminations in (from top to bottom) Experiments IC, SIC, IC_A, and SIC_A. From left to right the columns show the results for standard and match illumination pairs D65/D40, D65/D200, and D40/D200. In each plot the coordinates of these two illuminations are shown by an open square and an open circle, respectively. The small red, green, and blue crosses mark the coordinates of the background colors seen through the filter of the respective hue in the standard stimulus, the large crosses the corresponding coordinates in the comparison stimulus. The colored disk, box, and diamond symbols show the setting for filters with a clarity parameter $C = 0.5, 0.75, \text{and } 1.0$, respectively. Coincidence of these symbols with the large crosses of the same color would indicate complete constancy. The dashed lines show the predictions for daylight illuminations in the range from 3000–20,000 K. All coordinates are in CIE (1976) $u',v'$ chromaticity space. See text for details.
conditions involving illumination changes. The latter result is surprising, given that the transmittance parameter of the filter model is illumination invariant (see Equation 4) and that a high degree of constancy under illumination changes was found in the simulation study (see Figure 8).

The kind of deviations from constancy found under illumination changes can best be visualized in the uvs-UV-chromaticity space: Each of the 12 diagrams in Figure 14 summarizes the predictions and the actual results for all nine filters under one of the three illumination changes investigated in one of the four experiments IC, SIC, IC_A, and SIC_A. In each diagram, a black open square marks the chromaticity of the mean background color in the standard stimulus and a black circle the corresponding value in the comparison stimulus. Under the assumptions used in the experiment, these are identical to the chromaticities of the illuminations used in the standard and comparison stimuli and are therefore always located at different positions on the daylight locus. Applying a specific filter to the background colors while ignoring the direct reflection component amounts to multiplying each background color \( A_i \) (component-wise) with the transmittance vector \( \tau \), that is, the transformed color \( \hat{A}_i \) is given by \( \tau A_i \). In the following, we will call these values raw filtered colors. The chromaticity of the mean of \( \hat{A}_i \) is shifted away from the mean of \( A_i \) and this shift depends in a unique way only on the hue \( H \) and saturation \( S \) parameter of the filter. The position of the mean raw filtered color of the standard stimulus under the reddish, greenish, and blueish filters are shown in the diagram as small red, green, and blue crosses, whereas the positions of the mean raw filtered colors in the comparison stimulus predicted for the same filters are marked by large crosses. Thus, under complete constancy the subjects’ settings should coincide with the large crosses in each diagram. In most cases, the actual settings shown as colored symbols in the diagrams deviate systematically from this prediction and these deviations increase slightly with a decreasing C-parameter of the filter. These deviations are obviously of a very regular nature: In each case the mean of the filtered colors derived from the settings can be described as a compromise between the predicted mean color under complete constancy and the mean color presented in the standard stimulus. Figure 15 demonstrates the meaning of this compromise on the stimulus level.

As a convenient index for the degree of constancy, the Brunswick ratio \( r = |D - S|/(|P - S|) \) can be used (Leibowitz, 1956), where \( D \) denotes the actual setting, \( P \) the predicted setting under complete constancy, \( S \) the predicted setting under a proximal match, and \( |x - y| \) the distance between \( x \) and \( y \) in the UV-chromaticity space. The index is one if the subject’s setting coincides with the prediction under complete constancy and zero for an exact proximal match.

Figure 16 compares the Brunswick ratios found in the four experiments with illumination change. They are almost evenly distributed in the range [0.2, 1] with a total mean across all experiments of 0.57. The comparison between simultaneous and alternating presentation modes shown in the top row of Figure 16 reveals that in all 27 experimental conditions the constancy index under the alternating presentation mode was at least as large, and often considerably larger, than that found under simultaneous presentation mode. The comparison between the experiments with identical presentation mode shown in the lower row of Figure 16, on the other hand, indicates that it does not matter much whether only the illumination changes between standard and comparison (IC) or also the background colors (SIC). This confirms the insensitivity of transparency perception to changes in background colors found in experiment SC.

Predicting asymmetric matching results

In this section we will explore quantitatively how well a compromise between a proximal and a constancy match actually predicts the subjects’ settings. To this end we first specify concrete mixture models that are then fitted to our data and compared with respect to the size of the residuals.

A simple mixture model

The deviations from constancy found in our experiments for clarity values of 0.5 and 0.75 were of similar size as those found with a clarity value of 1, where the direct reflection component vanishes. We therefore assume that the compromise is formed with respect to the core multiplicative part of the filter model, which describes how the color codes of the background change due to the transmissive properties of the filter. If \( (A_j, P_j) \) and \( (B_j, Q_j) \) denote the background and raw filtered color codes in the standard and the comparison stimuli, respectively, then this core part of the model simply states that for the \( j \)th color pair, it holds that \( P_{ji} = \tau_{0j} A_{ji} \) and \( Q_{ji} = \tau_{1j} B_{ji} \), with \( i = L, M, S \). The proximal match criterion is achieved if the mean color of the filter region in the comparison stimulus—denoted \( X_P \) and \( X_C \) for the proximal and the constancy criterion, respectively—and because \( \tau_i = Q_i / B_i \) is a specific transmittance vector. The simple mixture model
we want to propose states that the compromise is found by computing a weighted average $Y$ between $X_P$ and $X_C$ and that this value is used to compute a corresponding transmittance vector $\hat{s}_{1i} = Y_i/B_i$. To get an idea how the mixture is actually done, it is helpful to have a look at our data: The left panel in Figure 17 reproduces nine matches already shown in Figure 14. The small and large crosses show the chromaticity of the mean raw...
filtered color in standard and comparison stimuli which correspond to the above defined colors $X_P$ and $X_C$, respectively. The filled symbols are the actual settings of the subjects (for red, green, and blue filters with different values in the clarity parameter). The interesting aspect in the present context is that the subjects’ settings seem to deviate systematically from the straight dashed lines in the plot, which correspond to the chromaticities of a convex mixtures $Y = (1 – z)X_P + zX_C$, $0 \leq z \leq 1$, between $X_P$ and $X_C$, and to follow instead more closely the curved dashed lines. These curved lines have the same meaning as in Figure 14, that is, they show how the means of the raw filtered colors change under variations in the color temperature of the illumination. The blue curve corresponds approximately to the daylight locus. If the data are replotted in a log rb-MacLeod-Boynton chromaticity space (see right panel of Figure 17), these curved lines are approximately straight. This observation indicates that the mixture is done in a log space, that is, that $Y = \exp[(1 – z) \ln(X_P) + z\ln(X_C)]$. In the following we will use the names Mix and LogMix to refer to these two models.

**Parameter estimation**

Both mixture models have a single parameter $z$ that determines the relative weight of $X_P$ and $X_C$, where a value of $z = 0$ indicates a proximal match ($Y = X_P$) and a value of $z = 1$ a constancy match ($Y = X_C$). If the match is actually a compromise between these two extreme cases and if one of the mixture models describes this compromise correctly then it should be possible to reproduce the subjects’ settings (up to random errors) by choosing an appropriate mixture weight $z$. Furthermore, if one considers the complete set of 27 settings made in each experiment, there are again two extreme cases, namely, on the one hand, that a good approximation requires a different $z$ for each setting or, on the other hand, that a single $z$ suffices to described all settings. Intermediate cases, where certain subsets of data share a common $z$ are also possible.

Constrained minimization was used to find the best fitting $z \in [0, 1]$. The loss function to be minimized was the squared distance between the colors (cone excitations) in the filter region of the comparison stimulus set by the subjects and the corresponding colors predicted by the filter model in combination with one of the mixture models. The actual procedure is described in Appendix A.

To evaluate the performance of the models, we consider the residuals of the mean raw filtered colors chosen by the subjects relative to the model predictions in the uv-chromaticity space. If these residuals are due to random errors, then they should be nearly symmetrically distributed around zero, because the uv-chromaticity diagram is approximately a uniform color space. Figure 18 illustrates the results for a subset of the data in detail. The plots show the distribution of the residuals of all 27 mean settings made in Experiment IC_A with respect to the predictions assuming complete constancy (blue open symbols) and with respect to the best fit of different mixture models (red symbols). For both models the residuals are indeed approximately symmetrically distributed around zero and the variance is much reduced compared with that of the blue symbols. However, in the case of the Mix model the mean of the residual distribution is slightly shifted to the left. This bias, which is absent in the LogMix distribution, is due to the systematic deviations of the settings from a convex mixture mentioned above and illustrated in Figure 17. The right panel in Figure 18 shows the change in the residual distribution of the LogMix model if only three different $z$ (one for each filter hue) are allowed instead of 27. Although the increase in the variance of the distribution is clearly noticeable, the prediction is still rather good.

Figure 19 shows the mixture weights $z$ resulting from the fits of the LogMix model with 27 and three different values (the residuals of these fits are shown in the two panels on the right side of Figure 18). These $z$ values can be interpreted as constancy indices and as such pose an alternative to the Brunswick ratios used in Figure 16.

Figure 20 presents, in condensed form, a more complete picture of how well the subjects’ settings can be described by the mixture models. It summarizes the results of all four experiments with illumination changes, that is, each bar shows the mean parameter value of four distributions with 27 residuals each. In these plots it is obvious that the Mix and LogMix models are comparable with respect to the variance of the residual distribution, but that the Mix model leads to a systematic bias. The size of the residuals of the LogMix model are comparable to those found in Experiment SC, when one allows for a different $z$ in each setting. This suggests that these residuals are best considered to reflect random errors. A comparison between the residuals for different groupings indicates that only filter hue has a strong systematic influence on the size of the mixture weight $z$, whereas filter clarity has only a small and illumination color barely any effect. Figure 19 suggests that in our experiments mainly the blue filter differed from the green and red one with respect to the degree of constancy.

**Discussion**

The results indicate almost complete constancy of the filter parameters under changes in background colors (scene constancy) but systematic deviations from
constancy if the context change includes a change in the color of the illumination. These deviations were mainly restricted to the hue and saturation parameter of the filter model and a closer inspection of the deviation pattern suggests that the subjects’ settings represent a compromise between a constancy match (corresponding to the predictions of the filter model) and a proximal match that uses similarity of the mean color in the filter region as a criterion. The finding that the results can almost perfectly be described by a specific mixture model (LogMix) if a separate mixture weight is allowed for each setting confirms this hypothesis.

**Possible reasons for the deviation from constancy**

The settings made in the experiment were highly reliable and very similar across subjects. Together with the fact that the subjects’ ratings of the quality of the match were high throughout, this suggests that the cross context matching realized in the experiments was a well defined task that posed no serious problems to the subjects. It is therefore very unlikely that the observed deviations from constancy can be ascribed to problems in achieving a satisfactory match similar to those that have been observed in asymmetric color matches (Logvinenko & Maloney, 2006). The deviations from constancy under illumination changes can

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**Figure 17.** Plot of the same matches in the UV chromaticity space and in a logarithmized version of the MacLeod-Boynton rb chromaticity space (MacLeod & Boynton, 1979). The curved lines in the left plot are approximately straight in the right one. See text for details.

**Figure 18.** Error distributions relative to the predictions of complete constancy and relative to the predictions of the mixture models. In each plot the blue open symbols are the residuals of the 27 mean settings made in Experiment IC_A relative to the predictions of the filter model, that is, complete constancy. The red dots are the residuals relative to the predictions of a best fitting mixture model and the circles are the $3\sigma$ error ellipses for this residual distribution.
also not easily be attributed to incomplete stimulus information or uncertainties in the estimation procedure because the simulation study reported in the section called Constancy from a computational perspective suggests that the visual system could in principle do much better.

This clearly indicates that the observed deviations of the subjects’ settings from constancy as predicted by the filter model are not mere experimental artifacts. It may be tempting to conclude from this discrepancy that the filter model is simply the wrong approach and cannot be used to describe transparent layer constancy.

Figure 19. Estimates of the mixture weights $\alpha$ for the LogMix model with 27 different weights (left panel) and with the restriction to three different weights, one for each filter hue (right panel). The residuals of the corresponding fits are shown as red dots in the middle and right panels, respectively, of Figure 18.

Figure 20. Mean parameters of the residual distribution in the four experiments with illumination change for the Mix and LogMix model and different groupings of the data. The top panel shows the distance of the distribution mean form zero (bias), the bottom panel the length of the major axis of the $3\sigma$ error ellipse (variance). The dashed horizontal lines are the corresponding values found in Experiment SC without illumination change. See text for details.
Indeed, this conclusion seems almost unavoidable, if one assumes (as is often tacitly done in vision) that phenomenal impressions reflect in a unique and unbiased way the visual system's response to the current proximal stimulation; because if this were true, one would expect that the degree of constancy found in the phenomenal match should be roughly identical to that predicted by the putative cue model.

We prefer an alternative interpretation, though, and see the key to understanding the deviations in a distinction between representational and phenomenal constancy. Figure 21 illustrates the key elements of this view. This distinction rests on the assumption that the main purpose of vision is to activate internal representations that stand for the system's interpretation of the current input and that are used in the planning and execution of task-related actions (Hoffman, 2009; Koenderink, 2011; Mausfeld, 2011). Phenomenal impressions, on the other hand, are considered as a conscious output of vision that serves specific purposes. A characteristic property of phenomenal impressions seems to be that they always retain a great similarity to the proximal stimulation. Figure 22 illustrates this in the domain of size constancy. A possible functional explanation of this property could be that phenomenal impressions are used to retain information about the kind of input that led to the current scene interpretation.

An important consequence of this distinction is that constancy on the representational level (i.e., invariance of the activated representation and their related parameters) does not imply phenomenal constancy (i.e., invariance of appearance) and vice versa. Or, put in another way, lack of complete phenomenal constancy does not exclude the possibility that there exist internal representations or unconscious outputs, for instance those that are involved in action control, that manifest more complete levels of constancy. From this perspective, the divergence between the simulation results and the psychophysical data are not inconsistent with our model because the simulation tests a cue model and thus refers to representational constancy, whereas the experiments, in which we asked the subjects to match the filter in appearance, refer to phenomenal constancy. Our simulation results would then indicate that almost complete constancy is possible on the representational level, whereas the experiments show that constancy on the phenomenal level is incomplete.

If this interpretation is correct, then one would expect to find similar deviations from constancy in other domains. And indeed, it has often been observed in investigations of form, size, and color constancy that phenomenal impressions show a much lower degree of constancy than the corresponding scene interpretation. If, for instance, a circular disk is increasingly tilted relative to the viewing direction, its interpretation as a circular object remains constant over a large angular range, whereas the phenomenal impression is almost immediately that of an ellipse. Although the phenomenal impression is usually distorted in the direction of the true interpretation ("regression to the real object," Thouless, 1931), the correction is often relatively small.
The compromise reflected in our data may therefore be understood as just another instance of a “phenomenal regression to the real object”, where the prediction derived from the filter model (denoted $X_C$ in the section called Predicting asymmetric matching results) is taken as the real object and the mean color in the filter region (denoted $X_P$) as the proximal information. The finding that the subjects’ settings always lay on a simple connecting curve between $X_P$ and $X_C$ supports this interpretation.

**Possible influences on the constancy index**

The constancy indices were very similar for different subjects, but varied considerably across the 27 conditions investigated and were consistently higher in alternating than in simultaneous presentation mode. Together, these findings suggest that the compromise is made in a very systematic way that depends mainly on objective properties of the experimental setting. It is therefore worthwhile to consider possible factors that may influence the degree of constancy observed in phenomenal matches.

We first consider possible causes for an increase in the constancy index under alternating presentation mode. Empirical evidence suggests that the degree to which the phenomenal impression is distorted toward the real object increases with the plausibility of the scene interpretation (Holway & Boring, 1941). Accordingly, the systematic increase of the constancy index observed under alternating presentation mode may partly be attributed to an increased plausibility of an illumination change in this condition. This effect may be supported by a simultaneous weakening of the influence of the proximal contribution, resulting from the fact that standard and comparison stimuli can no longer be directly compared if presented in alternation.

Obviously, a different explanation is needed for the variation of the constancy index across the 27 conditions realized within each experiment. Possible explanations may be related to the fact that the constancy index is computed as a relation $||D - S|| / ||P - S||$. A first problematic point is that the empirical value is determined on a nominal scale and not on the (unknown) perceptual scale, which is the actually relevant one. If the relation between the nominal and the perceptual scale is nonlinear, then equal constancy indices computed on the nominal scale are in general different on the perceptual scale and vice versa. The larger the variation in $||P - S||$ the more pronounced the effect of a nonlinearity would be and the larger the observed variance in the constancy index. A second, more fundamental problem may be that the distortion of the phenomenal impression in the direction of the true object is essentially constant in absolute terms and not—as is implicitly assumed in the construction of the constancy index—in relative terms. This was, for instance, roughly the case in the experiment on form constancy conducted by Thouless (1931). As a consequence, the constancy index as defined above would decrease with an increasing distance between $P$ and $S$. Thus, if one assumes that the phenomenal distance between $P$ and $S$ (i.e., between $X_P$ and $X_C$ as defined in the section called Predicting asymmetric matching results) was different across the 27 conditions, then the two mentioned factors could at least partly explain the observed variation in the constancy index. This assumption does not seem unreasonable, given that differences in filter hue explain a large portion of the constancy index variance in our experiment. However, due to the unknown metric of color space, it is difficult to explicitly test this hypothesis based on our data.

To put these points in perspective, we should note that results from extensive informal tests suggest that the differences in mixture weights found in the experiments are noticeable but not very pronounced in absolute terms. In these tests, we compared a large number of random filter pairs under different random illuminations in displays similar to those used in the experiments and found that a mixture weight of about 0.5 leads in most cases to impressions that very closely approximate phenomenal constancy.

**Relation to the findings of Khang and Zaidi (2002a)**

The experiment of Khang and Zaidi (2002a) was similar to ours in that subjects matched the appearance of filters presented on different backgrounds. The main methodological differences are that the background colors in the standard stimulus were computed from biased reflectance distributions under equal energy illumination and therefore had a nonneutral mean, that the filters were simulated based on a convex mixture of seven arbitrarily selected standard transmittance curves, that only filters without direct reflection part were used, and that the colors of the match background were always different shades of gray. The authors report to have found surprisingly constant matches with only a few systematic deviations from “a veridical match”. How does their findings relate to those presented here?

From the perspective of our approach, the mean of the background color is used (at least in simple scenes) to infer the illumination color. Thus, although the authors simulated a neutral illumination in both standard and match background, this would mean that the visual system may nevertheless assume a different illumination in standard and match. Their results should therefore be related to the ones found in our conditions with illumination change. The change in illumination is, however, less pronounced than in our
observation, because the deviations of the mean of the standard background from the neutral point were relatively small and the mean of the match background was always neutral. It is therefore not surprising that deviations from constancy were often relatively small in absolute terms. However, their figure 6 in which veridical matches (roughly comparable to $X_C$ in our notation) and the no scission predictions (corresponding to our $X_P$) are compared with the actual settings reveals a pattern that is roughly compatible with our findings: The actual settings are also in most cases intermediate between $X_C$ and $X_P$. Their results seem slightly less regular, though. This may be due to the fact that the filter model predicts perceived transparency better than the physical model (see Faul & Ekroll, 2011, Experiment 1). Thus, the predictions based on the filter model that we used may be more reliable than the ones based on the physical model that were used by Khang and Zaidi (2002a).

**Related findings in investigations of color constancy**

Transparent layer constancy under changes in illumination and color constancy are closely related problems and it is therefore not unexpected that results similar to ours have been found in color constancy: If subjects match the color of two targets embedded in differently illuminated mondrians that are presented side by side then incomplete constancy is observed with constancy levels ranging from 40% to 80% (Reeves, Amano, & Foster, 2008). If the two mondrians are instead presented sequentially at the same place then significantly higher levels of constancy may result (Foster, Amano, & Nascimento, 2001). Foster et al. (2001) discuss the role of temporal transient cues as a possible explanation for the latter finding. However, as an explanation of our similar results this seems less plausible because here the sequentially presented stimuli were located at different screen positions.

Of some relevance for the distinction between phenomenal and representational constancy made above is the fact that the level of color constancy that is found in experiments depends strongly on the task that was used. In the approach illustrated in Figure 21 this may be explained by task specific mapping functions $g(X, Y, \ldots)$. Arend and Reeves (1986), for instance, found much lower levels of constancy in a task that requires to match the local colors (both targets “have the same hue and saturation”) than in a more abstract task that referred to scene interpretation (both targets “are cut from the same piece of paper”). Craven and Foster (1992) report that subjects can quickly and with high reliability decide whether color changes between two scenes are due to a change in illumination or due to a change in reflectance. In this task, which mainly refers to scene interpretation, also high levels of constancy have been found (Reeves et al., 2008).

**Bayesian modeling**

Above, we considered the possibility that the increase in constancy observed under alternating presentation mode may be due to an increased plausibility of an illumination change in this condition. As suggested by one of the reviewers, Bayesian decision theory (Maloney & Zhang, 2010) may provide a useful framework to capture this idea in a more principled way. The general idea is that the visual system is confronted with the uncertainty regarding whether the color changes in the stimulus are due to illumination change or not. The compromise found in our data may then result from an attempt to minimize the expected cost of getting the
interpretations and the certainty of the visual system.

Summary and general discussion

When we perceive transparency, the stimulus is separated into a background component and a transparent layer with clearly defined properties like thickness, transmittance, or color. The basic question we addressed in this paper was to what extent the properties ascribed to the transparent layer remain constant under changes in context, in particular changes in the structure of the background seen behind the layer and changes in the prevailing illumination.

In our investigations we referred to a filter model of perceptual transparency (Faul & Ekroll, 2002) that is meant to describe a cue that uses regularities between color codes to infer transparency-related parameters of internal representations. This interpretation as a cue is supported by previous results in which we have shown that the filter model describes color changes caused by optical filters to a good approximation, that the parameters of the model can be computed from the input in a robust way, and that these parameters stand in a regular relationship to physical parameters of optical filters and—after a suitable transform—also to phenomenal dimensions of transparency impressions (Faul & Ekroll, 2011).

Our first aim was to test constancy at the cue level in a computer simulation: If the model actually describes a color-related cue to transparency then one would expect that the response to a fixed target object (reflected in the model parameters) should be largely invariant under changes in context. To test this we computed the proximal stimuli caused by a fixed optical filter under a range of illuminations and background reflectances. From this input the parameters of the filter model were computed and constancy was measured by the variance of the estimated parameters. Almost complete constancy was found when the number of background colors was not too low. This suggests that the color relations described by the filter model can indeed be used as a very reliable cue to detect optical filters and to distinguish between different instances of such objects.

In six closely related experiments we used cross-context matching to investigate how phenomenal transparency is influenced by context changes similar to those studied in the computer simulation. That is, standard and comparison stimuli again differed with respect to the background reflectances and/or the simulated illumination. If the context change was restricted to changes in background reflectances, almost complete constancy was found, that is, the parameters of the filter shown in the standard stimulus and the parameters of the filter chosen by the subjects in the comparison stimulus were almost identical. In all conditions with illumination changes, however, the subjects’ settings deviated systematically from constancy. However, these deviations were of a very regular nature: The mean color in the filter region of the subject’s setting was always a mixture between the mean filtered color expected under complete constancy and the mean filtered color in the standard stimulus.

We interpret these results as another manifestation of a “phenomenal regression to the real object” (Thouless, 1931). Accordingly, the deviations from constancy are not taken to indicate erroneous estimates due to a lack of information or imperfections in the estimation procedure but are interpreted as a consequence of a characteristic property of phenomenal impressions in vision, namely that they always retain a close relationship to the properties of the proximal stimulation: If a stimulus element is first presented in isolation and afterwards embedded in a context that prompts the visual system to assign a scene interpretation to the stimulus element, then the impression under context-free presentation is distorted in a direction that enhances the compatibility with this scene interpretation, but this distortion is normally far from complete. This does not prevent, however, that different degrees of constancy are found in other representations. The scene interpretation itself or vision guided actions, for instance, may at the same time reflect almost complete constancy.

Theoretical considerations and empirical evidence suggest that constancy is a multifaceted concept. Phenomenal impressions have been found to reflect only a limited form of constancy, whereas the usually successful interaction of organisms with the environment suggests that other subsystems are more robust. From this perspective, the present results from direct cross-context matches with phenomenal instruction provide only a fairly incomplete picture of transparent layer constancy. A more complete account thus requires the use of other tasks that are closer related to the scene interpretation derived from the input. Khang and Zaidi (2002b), for instance, used identification of filters across illumination changes as a constancy criterion and report a highly reliable performance. Another promising alternative may be to use more complex matching tasks that require the subjects to reproduce a given relation between objects in a standard context in a comparison stimulus with other context conditions (for a review of similar approaches in color constancy, see Brainard, 2004). Potentially useful cross context tasks may be to identify a certain object in a set of objects, to sort objects along certain dimension, or to select objects that stand in a certain quantitative relation to others.
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References


Appendix A: A procedure used to fit the mixture models

The procedure used to compute the error for a given \( z \) value was as follows: (a) Compute \( X_P \) and \( X_C \) from the known background colors and \( \tau_0 \), the
transmittance factor, computed from the standard stimulus. (b) Compute an intermediate color \( Y = f(\alpha, X_P, X_C) \), where \( f \) is one of the mixture models. (c) Compute an estimate \( \hat{\tau}_1 \) of the transmittance factor with \( \hat{\tau}_1 = Y_i / B_i \). If \( \max(\hat{\tau}_i) > 1 \), which would violate a constraint on \( \tau \), divide \( \hat{\tau} \) by \( \max(\hat{\tau}_i) \). (d) Compute the predicted filter color using \( \hat{F}_{ji} = \hat{\tau}_1(B_{ji} + \delta_0 B_i) \), with \( \delta_0 = 1/C_0 - 1 \) where \( C_0 \) is the clarity parameter used in the standard stimulus. Note that this is the reduced filter model including the direct reflection component. (e) Compute the loss function \( Err(\alpha) = \sum_i (F_{ji} - \hat{F}_{ji})^2 \), where \( \hat{F}_j \) is the predicted color in the filter region of the comparison stimulus and \( F_j \) the corresponding mean color set by the subjects. To compensate for different scales in the three color channels, both \( \hat{F} \) and \( F \) were first component-wise divided by the relative cone excitations values of an equal energy white.