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Age-Specific Perceptual Image Quality Assessment

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Abstract

With the development of image-based applications, assessing the quality of images has become increasingly important. Although our perception of image quality changes as we age, most existing image quality assessment (IQA) metrics make simplifying assumptions about the age of observers, thus limiting their use for age-specific applications. In this work, we propose a personalized IQA metric to assess the perceived image quality of observers from different age groups. Firstly, we apply an age simulation algorithm to compute how an observer with a particular age would perceive a given image. This age simulation algorithm adapts the input image according to an age-specific contrast sensitivity function (CSF), which predicts the reduction of contrast visibility associated with the aging eye. Then, we combine the age simulation algorithm with existing IQA metrics to calculate the age-specific perceptual image quality score. To validate the effectiveness of our combined model, we conducted psychophysical experiments in a controlled laboratory environment with young (18-29 y.o.), middle-aged (30-54 y.o.), and older (55+ y.o.) adults, measuring their image quality preferences for 84 test images through pairwise comparisons. The statistical analysis shows that the predictions by our age-specific IQA metric are well correlated with the collected subjective IQA results from our psychophysical experiment.

Introduction

Image quality assessment (IQA) is the process for measuring the perceived image quality by human observers. Due to age-related changes to our visual system, different age groups have different quality perceptions of the same image. However, most of the existing IQA metrics make simplifying assumptions about the age of observers, and existing IQA datasets do not record the precise age information of the observers. These aspects limit the application of IQA for age-specific tasks.

In this paper, we present an age-specific IQA model to predict the perceived image quality of observers from different age groups. As depicted in Figure 1, our model consists of two components: an age simulation algorithm to determine how an observer of a particular age would visually perceive an image, and an IQA metric to compute the associated age-specific image quality score. The age simulation algorithm is based on contrast matching and we evaluated two different contrast matching models.

We then conducted psychophysical experiments to validate the effectiveness of our combined model. Finally, we performed statistical analysis on our validation results and get a Pearson correlation coefficient of 0.764, which indicates a strong correlation between our model prediction and the human perception. The p-value is less than 0.01, which shows that our conclusion is statistically significant.

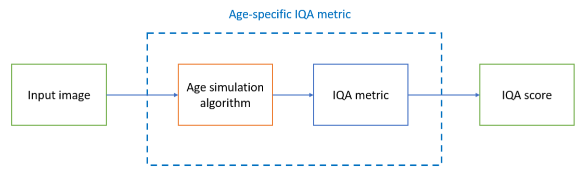


Figure 1: Age-specific IQA metric.

Our model can be applied in numerous scenarios. It can be used to predict the image viewing experience without having to perform the subjective evaluation. It can be used as a training loss for neural-network-based models. It can also be applied in image enhancement algorithms.

Related Work

Our age-specific IQA model applies the knowledge of the aging vision to existing IQA metrics. Thus, we will review the previous research on IQA metrics and the aging vision.

IQA Metrics

IQA methods can be categorized into subjective and objective methods [1]. In subjective IQA, humans assign scores to images based on their perceived quality. This is the most accurate and reliable way to estimate the ground truth of image quality [2]. However, subjective IQA is time-consuming and inconvenient. Thus, objective evaluation methods are more widely-used to assess image quality.

There are three categories of objective quality assessment metrics, namely full-reference (FR), reduced-reference (RR) [3, 4], and no-reference (NR) [5, 6, 7]. FR requires the existence of a reference image, RR requires certain attributes from the reference image, while NR does not require a reference image.

Our age-specific IQA model falls into the category of FR IQA since the reference image is known. In our model, we apply a deep-neural-network-based IQA metric called the Learned Perceptual Image Patch Similarity (LPIPS) metric [8]. LPIPS uses a deep convolutional network originally pretrained for classification to extract feature embeddings for a given image. The authors compute feature embeddings for a reference and a test image, and estimate the similarity between them, which inversely correlates with the image quality of the distorted image.

Aging Vision

The human visual system degrades as we age. In order to develop personalized IQA metrics for a wider group of people, we need to understand the effect of aging on vision. Multiple aspects of human vision deteriorate with time, namely visual acuity [9, 10], contrast sensitivity [11], color vision [12], dark adaptation [13], and visual field [14]. For IQA, one of the most relevant effects of the aging visual system is the blurring of vision due to reduction in visual acuity and contrast sensitivity. While the visual acuity degradation can be offset by prescription eyeglasses, the contrast sensitivity degeneration, especially in the higher spatial frequency range, is more difficult to address and thus remains untreated [11]. Our age-specific IQA model thus mainly focuses on contrast sensitivity.

In general, the contrast sensitivity function (CSF) measures an observer's visual sensitivity over different spatial frequencies. CSFs also predict the observer's ability to detect just noticeable contrast. However, real-world scenes mostly consist of higher contrast levels, which is referred to as suprathreshold contrast. Various suprathreshold contrast matching models exist. For instance, the Kulikowski model [15] presented in the 1970s demonstrates a linearity in contrast perception: Kulikowski recognized that two contrasts appear the same to observers if the physical contrasts minus the threshold contrasts were the same. Some newer models [16, 17] believe the Kulikowski contrast matching model to be not adequate and that aging mostly affects the near threshold contrast vision instead of suprathreshold contrast vision. In our proposed IQA model, we will investigate both contrast matching models, and we term them the Kulikowski model and the suprathreshold model, respectively.

Methods

To implement the age-specific IQA model, we first simulate the image as perceived by an observer of a certain age, and then we use an existing IQA metric to predict the quality of the age simulation image. Validation of our model is achieved through psychophysical experiments for age-specific IQA.

Age Simulation

We adopt an age simulation algorithm that modifies the overall contrast visibility of a given image based on the known age-related CSF changes, thus allowing us to visualize the perceived image degradation associated with reduced contrast visibility due to aging. To this end, we apply the simulation method similar to the work presented by Wanat *et al.* [20].

We define a baseline reference CSF to be that of a 24-year-old observer. Our baseline CSF is from Mantiuk *et al.* [19], which provides the CSF data for a wide range of luminance values and spatial frequencies. Note that we set a constant luminance level of 200 cd/m^2. We then generate age-specific CSFs for age values ranging from 24 to 99 years old using the following empirical equation [18]:

$$\log_{10}(\Delta S) = -(\beta \log_2(\rho+\alpha)) \cdot \max(a-24,0) \tag{1}$$

where $\alpha = 0.75$ and $\beta = 0.00195$ are empirical parameters, ΔS is the sensitivity change, a is the age of an observer in years, and ρ is the spatial frequency in cycles per degree (cpd).

In what follows, we will explain how we apply age-specific contrast matching. To this end, we verify two different contrast matching models, the Kulikowski contrast matching model and the suprathreshold contrast matching model.

Kulikowski Contrast Matching Model

The contrast of an image can be defined using Michelson contrast as

$$c = \frac{L_{\max} - L_{\min}}{L_{\max} + L_{\min}} = \frac{\Delta L}{L_{\text{mean}}} \tag{2}$$

where $L_{\max}$ is the maximum luminance value and $L_{\min}$ is the minimum luminance value of a sine wave. ΔL is the modulation and L_{mean} is the mean of a sine wave.

The age-specific contrast detection threshold c_t can be predicted by the age-related CSF function as per Equation 3:

$$c_t = \frac{\Delta L}{L} = \frac{1}{S \cdot CSF(\rho, a)} \tag{3}$$

where S is the absolute sensitivity parameter, which can be adjusted to cater for different experimental settings (in our experiment, $S = 0.86$), ρ is the spatial frequency of the image, a is the age of the observer.

Kulikowski *et al.* find that two contrasts appear the same to observers when their physical contrast minus the threshold contrast are equal [15] as expressed by:

$$c - c_t = \tilde{c} - \tilde{c}_t \tag{4}$$

where c and $\tilde{c}$ are contrast magnitudes under different conditions, and c_t and $\tilde{c}_t$ are the contrast thresholds under the corresponding conditions.

Wanat *et al.* [20] show that the logarithmic contrast g defined as:

$$g = \frac{1}{2}\log_{10}\left(\frac{L_{\max}}{L_{\min}}\right). \tag{5}$$

also satisfies this relationship, except when the contrast is very high or the luminance is very low, which is uncommon for natural images and scenes. Thus, for natural images, we can apply the logarithmic contrast matching as follows:

$$g - g_t = \tilde{g} - \tilde{g}_t \tag{6}$$

where g and $\tilde{g}$ are logarithmic contrast magnitudes under different conditions, and g_t and $\tilde{g}_t$ are the logarithmic contrast thresholds under the corresponding conditions. Wanat et al. further demonstrate that using logarithmic contrast simplifies contrast matching calculations.

We use the CSF for a 24 y.o. as the reference CSF. In this setup, in order to show a 24-year-old person (with contrast threshold $g_{t_{24}}$) what an image would look like for an x-year-old person (with contrast threshold g_{t_x}), we need to reduce the contrast of the original image so that the contrast magnitude follows:

$$g_{new} - g_{t_{24}} = g_{ori} - g_{t_x} \tag{7}$$

where g_{new} is the contrast of the simulated image, and g_{ori} is the contrast of the original image.

The first step of our age simulation algorithms involves converting the input image to luma values as:

$$Y_{Luma} = 0.2126R + 0.7152G + 0.0722B \tag{8}$$

where R, G, and B are sRGB pixel values. We then compute luminance values $Y = Y_{Luma}^{\gamma}$, where γ is a characteristic of the display (i.e., the "gamma" of the display). In our model, we use 2 for a fast approximation.

We decompose the resulting luminance image L_{in} (Y) into a Laplacian pyramid, thus separating the image into non-overlapping frequency bands. When we apply the age simulation algorithm, we use the CSF data for a specific spatial frequency and apply the modification to each band separately. This approximation simplifies the age simulation algorithm while still providing a sufficient division of frequencies.

Every pixel in the Laplacian pyramid represents the local contrast, and the scale of the layer represents the corresponding spatial frequency. Since the constrast sensitivity threshold values are known from the age-specific CSFs, we can apply Equation 7 to produce a new Laplacian pyramid with adjusted pixel values, where the difference between the adjusted pixel value and its original value in the Laplacian pyramid is the same as the difference between the contrast detection threshold of a x-year-old and a 24-year-old at the corresponding spatial frequency, where x is the simulated age and 24 is the reference age. Finally, we can reconstruct an output luminance image L_{out} from the new Laplacian pyramid.

Note that if we switch the subtrahend and the minuend when calculating the difference, we will boost the contrast of the input image instead. Thus, we can also produce an age compensation algorithm. When an old person looks at the compensated image, they should theoretically have the same perceived contrast as when a young person looks at the original image.

Finally, we need to reconstruct the RGB image from the output luminance image L_{out}. From Equation 8, we can see that there is a linear relationship between the luminance value and the RGB values. Thus, we can simply multiply the RGB values of the original image with the ratio between the output and input luminance values at the corresponding location, as shown in Equation 9.

$$(R_{out}, G_{out}, B_{out}) = (R_{in}, G_{in}, B_{in}) \times \frac{L_{out}}{L_{in}} \tag{9}$$

where the R_{out}, G_{out}, B_{out} are the RGB values of the output image (i.e., the age simulation image). R_{in}, G_{in}, B_{in} are the RGB values of the original image. L_{out} is the output luminance of the image after age simulation/compensation. L_{in} is the luminance of the original image.

Suprathreshold Contrast Matching Model

As discussed in Related Work, recent research shows that Kulikowski contrast matching theory is not adequate. Thus, we introduce a second algorithm to perform suprathreshold contrast matching. Specifically, we apply a mask to filter out the image areas where the original contrast is already high. We then only apply the contrast adjustment to the remaining areas of the image where the original contrast is low. We set 0.3 as the threshold to apply the mask to separate the high and low contrast. This value is chosen heuristically and psychophysical experiments are conducted to validate this value. The contrast adjustment method is the same as described in the Kulikowski contrast matching method.

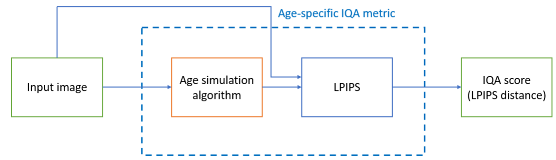


Figure 2: Age-specific IQA metric with LPIPS.

Note that in this method, contrast is adjusted only in some pixel positions. Thus, there will be luminance discontinuities at the boundaries of certain regions. However, this artifact is only significant for synthetic images where the contrast and spatial frequency change gradually. For natural images, the contrast and the spatial frequency change much more rapidly. Thus, this artifact is negligible for most natural images.

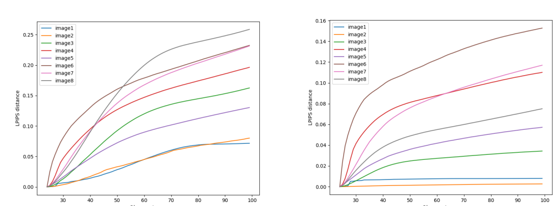
Age-Specific IQA Model

We combine the age simulation algorithm with a proven IQA metric and refer to the combination as the age-specific IQA model. Specifically, we use LPIPS as our IQA metric after the age simulation algorithm, as shown in Figure 2. LPIPS measures the distance between the feature spaces of the reference image and the distorted image (i.e., the age simulation image), which can be used as an indication of image quality. In our model, a large LPIPS distance between the reference image and the distorted image indicates low quality of the distorted image, and vice versa.

A simple test-case is presented in Figure 3: we evaluated our combined age-specific IQA model to calculate the image quality as a function of the observer's age ranging between 24 and 99 years of age, and using 8 different natural images. LPIPS distance increases with the observer's age, which is as expected given our empirical knowledge that as the observers get older, their perceived image quality decreases.

Model Validation

To validate the effectiveness of our age-specific IQA model, we designed a psychophysical experiment and then compared the predictions of our model versus the collected data. We conducted two sets of psychophysical experiments



(a) Kulikowski model. **(b)** Suprathreshold model.

Figure 3: LPIPS distance w.r.t. observer's age.

to test both the Kulikowski contrast matching model and the suprathreshold contrast matching model.

Psychophysical Experiment Design

We divide our observers into three age groups, namely the 18 - 29 y.o., 30 - 54 y.o., and 55 y.o. and above. We refer to our test subjects as young adults (i.e., 18 - 29 y.o.), middle-aged adults (i.e., 30 - 54 y.o.), and older adults (i.e., 55 y.o. and above) respectively.

We select 21 reference images with different contents including synthetic images and natural images. For each reference image, we generate four different processed images using the age compensation algorithm. Thus, there are 84 different test images. The processed images are compensated for 24, 40, 65, and 99-year-old observers respectively. We ask the observers to compare the images in pairs among the four aforementioned ages. Specifically, for the four processed images that are generated from the same reference image, there would be $\binom{4}{2} = \frac{4!}{2!(4-2)!} = 6$ pairwise comparisons for each observer. Thus, there are $21 \times 6 = 126$ pairwise comparisons in total for each observer.

During the psychophysical experiment, we show the 126 image pairs to the observers and ask them to choose the ones they prefer. After collecting observers' preferences, we average the answers of observers from the same age groups. We want to see how well the results from the psychophysical experiments correlate with the prediction from our age-specific IQA model.

The setup of our psychophysical experiment is as follows:

- Computer display resolution: 1920×1080.
- Computer display size: 16.5 cm $\times$ 29.4 cm.
- Computer display maximum brightness: 292 cd/m^2.
- Light bulb brightness: 800 Lumens.
- Ambient lighting color temperature: 5000 K.
- Ambient lighting at the display: 130 lux.
- Observer viewing distance: 70 cm.
- Visual angle: 13°.

Age-Specific IQA Model Predictions

We simulated four observers at 24, 40, 65, and 99 years of age. We used them to represent real observers from different age groups. The framework we use to predict the result of the psychophysical experiment is shown in Figure 4. Note that the transition across all age values is assumed to be gradual. Thus, we can use the response of an observer at the average age value to represent the average response of the corresponding age group.

We use the same test images as the ones that are used in our psychophysical experiment. For each reference image, we generate four different degrees of compensation (compensated at 24, 40, 65, and 99 years old). We then apply the corresponding age simulation algorithm on all four of the compensated images and set the simulation age to 24, 40, 65, and 99 years old. Thus, for each reference image, we will get 16 quality scores under different conditions. Finally, we take the average across all reference images.

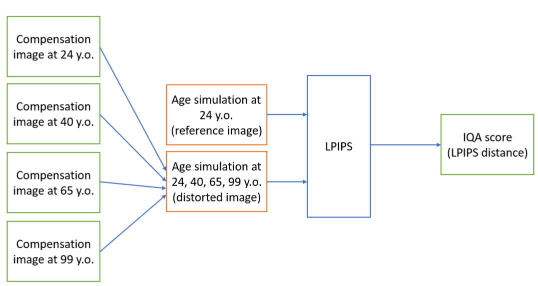


Figure 4: Simulating the outcome of the psychophysical experiment using our age-specific IQA model.

Results

In this section, we will show the prediction result for the psychophysical experiments using our age-specific IQA model, and then show the actual psychophysical experimental result. After that, we will conduct statistical evaluation to calculate the correlation between the above two results.

Psychophysical Experiment

We designed two sets of psychophysical experiments, one for each contrast matching theory. In the first psychophysical experiment where we applied the Kulikowski contrast matching theory [15], we tested 59 adults (38 males and 21 females) from 19 to 85 years of age and divided them into three different age groups to perform pairwise comparison tasks. There were 25, 19, and 15 participants in the young, middle, and older age groups respectively.

In the second psychophysical experiment where we applied the suprathreshold contrast matching [16, 17], we tested 59 adults (38 males and 21 females) from 19 to 76 years of age and divided them into three different age groups to perform pairwise comparison tasks. There were 25, 20, and 14 participants in the young, middle, and older age groups respectively.

During both of the psychophysical experiments, participants were asked to choose the image with higher image quality in their opinion in each pairwise comparison. For each participant, we calculate the percentage of votes they give to each compensation age value. Then we average the results among observers from the same age group. The result is shown in Table 1 and Table 2.

We also visualize the psychophysical experimental results in Figure 5. For the Kulikowski contrast matching method as shown in Figure 5 (a), we can see that the young adults prefer the compensation age at 24-year-old the most, while the middle-aged and older adults prefer the compensation age at 40-year-old the most. For the suprathreshold contrast matching method as shown in Figure 5 (b), we can see that the peaks of the preference curves are at 24-year-old compensation for young adults, 40-year-old compensation for middle-aged adults, and 65-year-old compensation for older adults. This means that the peak perceived image quality among young people is the compensated image at 24 years old; the peak perceived image quality among middle-aged people is the compensated image at 40 years old; the peak perceived image quality among older people is the compensated image at 65 years old.

Table 1: The percentage of votes an observer gives to each compensation age, averaged among the same age group. (Kulikowski contrast matching)

	24-year-old compensation	40-year-old compensation	65-year-old compensation	99-year-old compensation
Young	32.76%	32.03%	20.48%	14.73%
Middle-aged	20.05%	28.70%	26.27%	24.98%
Older	21.96%	27.57%	25.93%	24.55%

Table 2: The percentage of votes an observer gives to each compensation age, averaged among the same age group. (Suprathreshold contrast matching)

	24-year-old compensation	40-year-old compensation	65-year-old compensation	99-year-old compensation
Young	32.83%	28.35%	21.84%	16.98%
Middle-aged	22.82%	27.02%	25.87%	24.29%
Older	25.40%	25.68%	26.07%	22.85%

Age-Specific IQA Model Predictions

The expected outcome of the psychophysical experiment can be simulated with our age-specific IQA metric. Since we have two different contrast matching methods, we have two versions of the model prediction result.

The outcome of the model prediction using Kulikowski contrast matching is shown in Figure 6 (a). We can see that 24, 40, 65, and 99-year-old observers have the highest perceived image quality (lowest LPIPS distance) viewing the images compensated at 24, 40, 65, and 99 years old respectively. Also, we can see the minimal value in each curve increases w.r.t. the observer's age, which means the highest perceived image quality decreases as the age of observers increases.

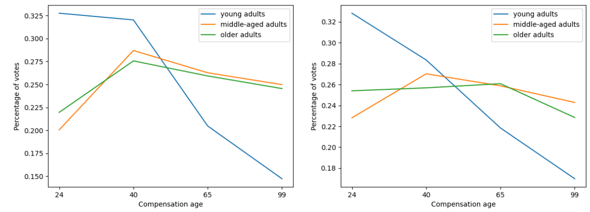
The outcome of the model prediction using suprathreshold contrast matching is shown in Figure 6 (b). We can see that a 24-year-old observer has the highest perceived image quality (lowest LPIPS distance) viewing the images compensated at 24 years old. There is no significant difference in our model prediction for the observers at 40, 65, and 99 years old. The most of the variance in the model prediction happens in the below 35 age range.

Statistical Evaluation

In this section, we will analyze how much of a correlation there is between our model prediction and the psychophysical experiment results using the Pearson's correlation coefficient.

In the psychophysical experiment, each level of compensation (i.e., each condition) is compared for the same number of times. Thus, we can directly use the observers' preference (i.e., percentage of votes) for a certain condition to represent the average quality score of images from that condition [25, 26]. Then we can calculate their correlation to the quality scores predicted by the LPIPS distance values.

Note that in the model prediction, we simulated a 99-year-old observer, but we did not conduct the psychophysical experiment on any people that belong to the 99-year-old age group due to the difficulty in recruiting older participants. Thus, we only have 12 corresponding data points to calculate the correlation coefficient instead of 16.



(a) Kulikowski model. **(b)** Suprathreshold model.

Figure 5: Results of the two psychophysical experiments by age groups showing the percentage of votes each participant gives to each condition (i.e., compensation age).

For the Kulikowski contrast matching model, the Pearson correlation coefficient is -0.761 which indicates a strong correlation between our model prediction and the psychophysical experiment results. The negative correlation is due to the fact that the LPIPS distance is lower for higher image quality (inverse relation). Thus, to make our results more straightforward, we report the positive correlation instead (i.e., 0.761). The p-value is 0.004, which means the correlation is statistically significant.

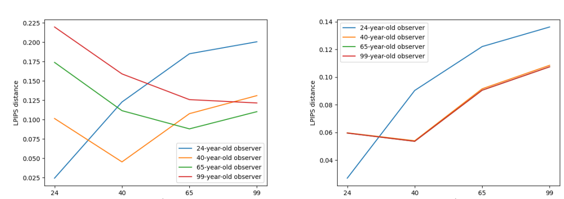
For the suprathreshold contrast matching model, the Pearson correlation coefficient is -0.764, and we also report the correlation coefficient as positive (i.e., 0.764) due to the reason described above. The p-value is 0.004.

Both of the contrast matching models give statistically significant predictions. For the suprathreshold contrast matching model, the Pearson's correlation coefficient is slightly higher than the Kulikowski contrast matching model.

Clustering Participants

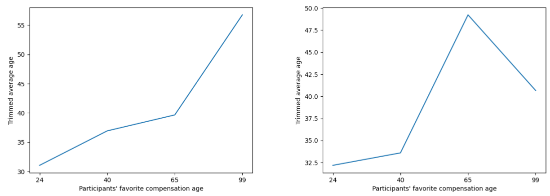
People age at different rates, and people's preferences vary a lot. Thus, we also attempted to cluster the participants not according to their biological age but rather according to their votes for each conditions. We calculate each participants' favorite condition (i.e., their compensation age), and cluster them into four different groups because there are four different conditions. We calculate the 10% trimmed mean of the age values of participants in each of the four clusters to avoid the influence of outliers. The result is shown in Figure 7.

In Figure 7 (b), when the participants' favorite compensation age is 99 years old, the corresponding average age is unreasonably low. Note that there is only one participant above 80 years old in our first psychophysical experiment, and no



(a) Kulikowski model. **(b)** Suprathreshold model.

Figure 6: LPIPS as predicted by our age-specific IQA model.



(a) Kulikowski model. **(b)** Suprathreshold model.

Figure 7: Results of the two psychophysical experiments showing the 10% trimmed mean age of each group clustered based on the participants' favorite compensation age.

participant above 80 years old in our second psychophysical experiment. Thus, the result for participants' preference for the 99-year-old compensation age (i.e., the last data point) is not accurate and should be discarded.

We then calculate the Euclidean distance between the mean age values in each cluster and the corresponding compensation age values. The Euclidean distance for Kulikowski contrast matching method is 26.48. The Euclidean distance for suprathreshold contrast matching method is 18.89. Note that the Euclidean distance values are calculated on the first three data points in each of the plot from Figure 7.

We can see that the trimmed mean age values have a higher correlation with the participants' favorite compensation age values at 24, 40, and 65 years old with the suprathreshold contrast matching model. This means for the three age groups that this study focuses on, the suprathreshold contrast matching method is better at modeling the aging affect on people's image quality perception compared with the Kulikowski contrast matching method.

Discussion

Prediction Analysis

In our age-specific IQA model, we implement two different contrast matching models, namely the Kulikowski and suprathreshold contrast matching. The predictions from both methods show a high correlation with the actual human response from the psychophysical experiments. The Pearson correlation coefficient for the suprathreshold contrast matching method is slightly higher than that of the Kulikowski contrast matching method. Moreover, when we cluster participants based on their favorite compensation conditions, we can see that the mean age correlates better with the compensation age in the suprathreshold contrast matching experiment. Thus, we can conclude that the suprathreshold contrast matching method is a better way to implement age-specific IQA.

Age-Specific IQA Model Limitations

1. In the age simulation model, we did not consider the image content and human attention. Observers may pay more attention to different parts of the image based on the image content. This might also affect the simulation outcome.

2. In the age simulation, we did not consider the CSF difference between foveal vision (for highly detailed information) and peripheral vision (for coarser information).

3. We represented each scale of the Laplacian pyramid with one specific spatial frequency. However, each scale of the Laplacian pyramid should consist of a frequency band. Thus, our simulation model is not precise when processing different spatial frequencies. This problem can be addressed by adding more scales in the Laplacian pyramid decomposition.

4. We implemented the Kulikowski contrast matching and the suprathreshold contrast matching methods. However, both of the contrast matching methods have limitations. From the experimental results, we can see that the peak value of our model prediction does not quite match with the peak value from our psychophysical experimental results, but both the model prediction results and the psychophysical experimental results show a clear split between young adults and the older adults. The limitation of our age-specific IQA model is two-fold. Firstly, the age simulation model we used focuses on the adjustment of contrast in an image. However, the perception of image quality depends on various other factors such as color saturation, personal preferences, and so on. Secondly, the LPIPS metric focuses more on calculating the difference in the feature space between the two input images, namely the reference image and the age simulation image in our model. The LPIPS metric is not adequate to detect the subtle contrast change in images, thus limiting its use in perceptual IQA.

Validation Limitations

1. In the validation section, we collected the age of the observers, but we do not take into account the covariants of the observers. To be specific, age may not be the only factor that affects the observers' perceived image quality. Other factors such as gender, cultural background may also affect the outcome.

2. We chose a specific psychophysical experiment setting with fixed display, ambient lighting, and viewing distance. Changing the psychophysical experiment setting might affect the experimental results.

Conclusion

We presented an age-specific IQA model that combines an age simulation algorithm with an IQA metric to predict age-dependent image quality perception. We validated our model through an extensive psychophysical experiment demonstrating strong correlation between our model's predictions and the collected subjective data.

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