# Image quality optimization, via application of contextual contrast sensitivity and discrimination functions

**Edward Fry**
**Sophie Triantaphillidou**
**John Jarvis**
**Gaurav Gupta**

Faculty of Science and Technology, University of Westminster

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Ed Fry, Sophie Triantaphillidou, John Jarvis and Gaurav Gupta
University of Westminster, Watford Road, HA1 3TP, Harrow, UK

## ABSTRACT

What is the best luminance contrast weighting-function for image quality optimization? 'Traditional' contrast sensitivity functions (CSFs) have been applied as weighting-functions in image difference metrics. This weighting also resulted in increased sharpness and color-preference, according to previous psychophysical research. We suggest 'contextual' CSFs (cCSFs) and 'contextual' discrimination functions (cVPFs) should provide bases for further improvement; these functions are directly measured from pictorial scenes, modeling threshold and suprathreshold sensitivities within the context of complex masking information. Image quality assessment is understood to require detection/discrimination of masked signals, making 'contextual' CSFs directly relevant.

In this investigation, images are weighted with a 'traditional' CSF, cCSF, cVPF and a 'constant' function. Controlled mutations of these functions are also applied as weighting-functions, seeking the optimal band weighting for quality optimization. Image quality, sharpness and naturalness are then assessed in two-alternative forced-choice psychophysical tests. Maximal quality, results from cCSFs and cVPFs, mutated to boost contrast in the higher visible frequencies.

**Keywords:** Image quality optimization, contrast sensitivity, contrast weighting-function, suprathreshold contrast, CSF, VPF

## 1. INTRODUCTION

Digital photographs are produced to be viewed by human observers, thus incorporating human visual system (HVS) models into image quality models is necessary for predicting visual quality. The application of contrast sensitivity functions (CSFs), as weighting-functions (see Triantaphillidou et al 2014 for a review) [1] when integrating the imaging system's spatial characteristics, prioritizes contrast information according to HVS detection to contrast, and attenuates frequencies outside the spatial limits of the HVS.

However, CSFs, whilst being very commonly used for the purpose, deal with contrast detection, thus the question on whether they are relevant to image quality modeling (which is concerned with suprathreshold visible contrasts) has been debated by many [1] [2] [3] [4]. Contrast detection (and contrast discrimination [1] [5]) functions do not account for upper-level cortical processing, which we expect to be of relevance in image quality analysis. So, are HVS models other than contrast sensitivity, or/and contrast discrimination functions, more suitable for application in spatial image quality modeling? According to Haun et al. [6], the quest for a standard spatial observer, which can make both qualitative and quantitative judgments from images, is a very complex matter.

This paper investigates the questions: *What are the optimum luminance contrast weighting-functions for image quality optimization; do they relate to threshold and suprathreshold sensitivity models?*

An initial background and recent CSF model developments are presented in Section 2. Section 3 describes our image capture and system characterization methods, used in psychophysical tests measuring quality, sharpness, and naturalness of images of natural scenes. Section 4 presents the modeling and mutation of threshold and suprathreshold sensitivity functions. Section 5 analyzes our image quality data, along with data collected from a short investigation of sharpness and naturalness. Finally, Section 6 discusses the relevance of contrast weighting-functions in image quality algorithms, and draws conclusions.

## 2. BACKGROUND

### 2.1 Recent developments of contrast sensitivity and discrimination functions

CSFs are traditionally measured from sine-wave gratings or Gabor patches, resulting in band-pass functions peaking at 1-4 cycles/degree for photopic vision. Neural noise affects all frequencies equally, lateral inhibition is responsible for their high-pass element, and the maximum number of integration cycles and optical modulation transfer function (MTF) limitations are responsible for their low-pass element [5]. Barten has produced a mechanistic CSF model based upon known measurements of sine-wave stimuli [5], which has been implemented into various image quality and difference metrics [7] [8] [9] [5] [10] [11]. Recent research has measured and modeled a new family of CSFs, as well as contrast discrimination functions (suprathreshold sensitivity functions), representing the contrast responses of the HVS to complex images [12] [13] [1]. These are the *Isolated Contrast Sensitivity Function* (iCSF), *Contextual Contrast Sensitivity Function* (cCSF) and *Contextual Visual Perception Function* (cVPF). They are shown below in Figure 1, for two of our test images, along with descriptions of the specific forms of sensitivity that they model (for further information see Triantaphillidou et al 2013 [13]).

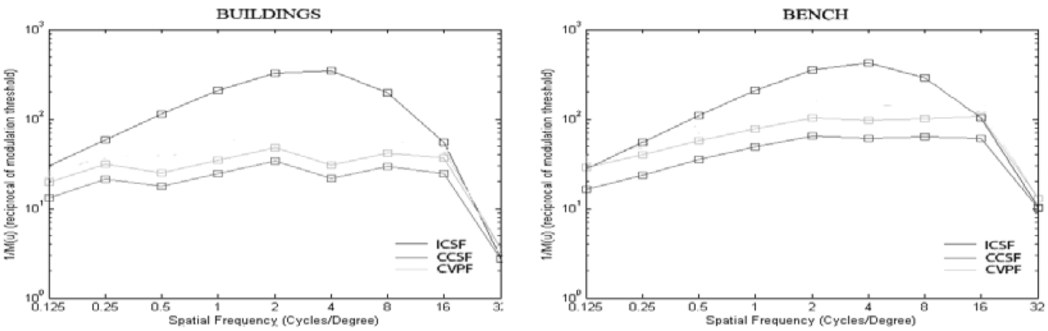


Figure 1. iCSF (black), cCSF (dark grey) and cVPF (light grey) for the 'Buildings' and 'Bench' images (shown in Figure 4).

1) iCSF describes the HVS' contrast detection threshold of a single band in isolation.
2) cCSF describes the HVS' contrast detection threshold of a single band, within the context of all other image bands (i.e. masked by suprathreshold information of other frequencies).
3) cVPF describes the HVS' discrimination sensitivity (suprathreshold sensitivity) to contrast differences within a single band, within the context of all other image bands.

These functions expand upon Barten's mechanistic model, and have been verified with extensive 2AFC pair-comparisons of band-altered images [12]. We expect them to be more applicable than 'traditional' CSFs, when modeling observations of the real-world or natural images, since these conditions expose the HVS to a plethora of complex frequencies. The contextual sensitivity (cCSF) and the equivalent discrimination function (cVPF) also account for the masking effects of complex signal information, which are relevant when searching for specific scene information embedded within images. The cCSF and cVPF show a different shape to the iCSF, as well as greater adaptation across different scenes, due to these masking effects (as shown in Figure 1).

### 2.2 Quality, contrast, sharpness, naturalness and their relationship

Image quality is defined as the integrated set of perceptions of the overall degree of excellence of an image [14]. Observed image quality is dependent upon the viewing conditions, the context within which the image is being viewed and the quality-consciousness of the observer [15]. It is common for photographers or automated image processing, to optimize the quality of raw images before display [16], by adjusting global contrast and sharpness independently. The proposed frequency domain contrast weighting method in this paper, adjusts the visibility of image frequencies, providing control over observed contrast and sharpness, which could be implemented into automated image processing algorithms.

In this paper, unless contrast is described specifically as observed contrast, it refers to root mean square (RMS) contrast, defined by the square root, of the mean of the squared deviation from the mean luminance. Recently, Haun and Peli [17] [2] have shown that the visual impact of suprathreshold contrast adjustments upon observed contrast, depends upon the frequency of the band to which they are applied. Their perceived contrast weighting functions are roughly band-pass in shape, peaking between 1.5 - 6 cycles/degree. Their shape and peak frequency depend upon image structure and observer's perceptions of the relative strength of contrast across the tested frequencies [17] [2]. These weighting-functions should not be confused with contrast weighting, as applied in our research, since the former represents observer's responses to contrast changes across different frequencies, whereas the latter provides specific weighting to the contrast of image frequencies, to produce an altered image. MacDonald and Bouzit performed a comparable investigation with respect to sharpness. They observed that the peak impact upon sharpness occurred when contrast was altered approximately 2 octaves above the peak of a standard CSF (for our test setup, this peak would be at approximately 16 cycles/degree [18]). According to both investigations, low or mid-frequency adjustments mainly affect observed contrast, while high-frequency adjustments affect sharpness.

Image sharpness, is associated with the abruptness of change of tone, at the edge of an object or tonal area [4]. Its presence in images results in greater three-dimensionality and clarity, and is of major influence upon observed image quality [18] [19]. Frequency-domain contrast weighting, is capable of compensating for contrast losses across the frequency domain, in comparison with an ideal system, which should theoretically increase fidelity and sharpness. These contrast losses are due to the capture/display system's point spread function (PSF), and are observable in MTF plots, which commonly show greater loss, with increased frequency. MacDonald and Bouzit successfully sharpened images, by compensating for the MTF of their display in comparison to an ideal system, as described in Section 2.3. This leads to our hypothesis: *'Weighting-functions, that boost contrast over the higher visible frequencies, should optimize image quality'.*

Image naturalness is a key factor in image quality assessment, and requires observers to reference their internal memory representations of the scene, under the assumed capture conditions [20]. Naturalness should not be confused with fidelity, since experiments investigating alteration of image chroma, discovered that perceptually natural images are generally not identical physical reproductions of the scenes they portray [21] [20]. Weighting of luminance contrast, as undertaken in our research, also affects image naturalness, and we expect the same relationship between fidelity and observed naturalness to apply. Pilot tests, showed that applying frequency-domain weighting-functions with poor image quality optimization performance, quickly led to naturalness deterioration. Slight over-application of the best performing weighting-functions, also reached a tipping-point where sharpness and/or quality improved, but naturalness deteriorated. This point varied across different scenes and weighting-functions. Thus, we feel it should be beneficial to understand the balance between sharpness, quality and naturalness, when assessing a weighting-function's ability to optimize quality. We have performed a small investigation into the relationship between naturalness, quality and sharpness, the results of which are shown in Section 5.3, and we intend to expand upon this in future research.

### 2.3 Development and variation upon previous contrast weighting optimization research

Our experimental method is based upon Bouzit and MacDonald's sharpness enhancement research [22]. Their research separated the luminance channel of YCbCr images, into log-ideal filtered image octaves, which provide fully independent band adjustment. In our research, band filtration of luminance was performed in the same color space, using Peli's log-cosine filters [23], since they introduce less ringing artifacts, whilst still permitting independent band adjustment. Our filters ranged from 0.125 to 32 cycles/degree for a viewing distance of 1.97m, with test images of 1794 by 1196 pixel dimensions, presented at a pixel pitch of 0.27mm. This minimized low and high-frequency residuals, which were added to the first and ninth filter respectively. Test images were cropped to 800 by 800 pixel dimensions after processing, to enable side-by-side pair-comparison in psychophysical tests.

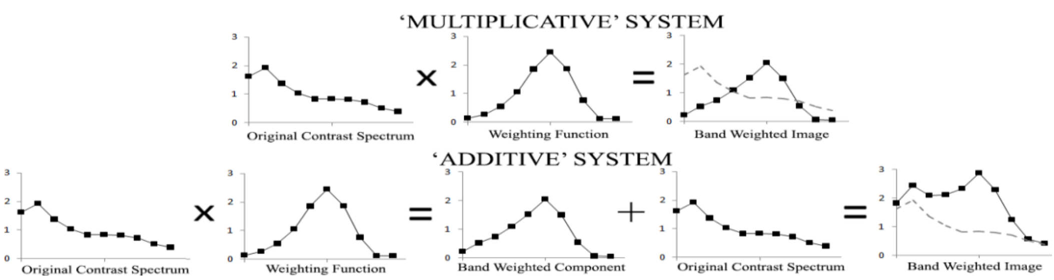


Figure 2. Description of 'multiplicative' and 'additive' weighting systems, showing comparison with the original band contrast spectrum (grey dashed)

The typical band weighting system multiplies image bands, with the normalized value of a CSF, calculated at each band's centre-frequency [7] [22] [5]. We observed losses in both low and very high frequency contrast, when using this *multiplicative weighting system* (Figure 2), due to sensitivity functions decaying in these respective frequencies. Total spectral power is also often reduced, due to loss of low-frequency contrast, since natural image contrast spectra generally decay with increased frequency in a *1/f* relationship [24]. Peli [25] suggests that the best CSFs for image quality modeling are flat at low frequencies, modeled from a low-pass filter, suggesting losses in low-frequency contrast are not beneficial.

We based our *additive weighting system*, on the spectrum characteristics of Photoshop's *Sharpen* and S*harpen-More* filters. They represent a standard for photographers, and were included as a benchmark in Bouzit and MacDonald's research, as well as our own. They provide an almost exponential boosting of contrast with increased frequency, with no contrast losses. Our proposed additive weighting system adds a band-weighted component to the original image, also resulting in boosted contrast with no losses (Figure 2). Therefore, contrast is boosted according to the HVS' capablability of detecting or discriminating it, within the context of the image, without reducing what we are less able to detect. This 'additive' weighting process shares similarities with the application of high-pass filters, or unsharp-masks to sharpen images [26], and it is a simple task to convert weighting-functions from this additive system to a conventional weighting system.

In a different investigation, MacDonald and Bouzit describe a frequency-domain sharpening process, by producing a high-pass function from the ratio of an ideal display MTF, and their display MTF [27]. A weighting-function was created by cascading the resulting high-pass function with the CSF, and increased image sharpness beyond the capabilities of Photoshop's USM (unsharp-mask) filter [27]. We describe a comparable process in Section 4.2, where we create mutation functions that are skewed towards the high frequencies, which are then cascaded into our band weighting process. This results in a basic sharpness and quality enhancement system, which relates directly to HVS detection and discrimination sensitivity, and becomes adaptive upon involvement of the cCSF or cVPF functions (Figure 8). Figure 3 describes the additive band weighting process in full.

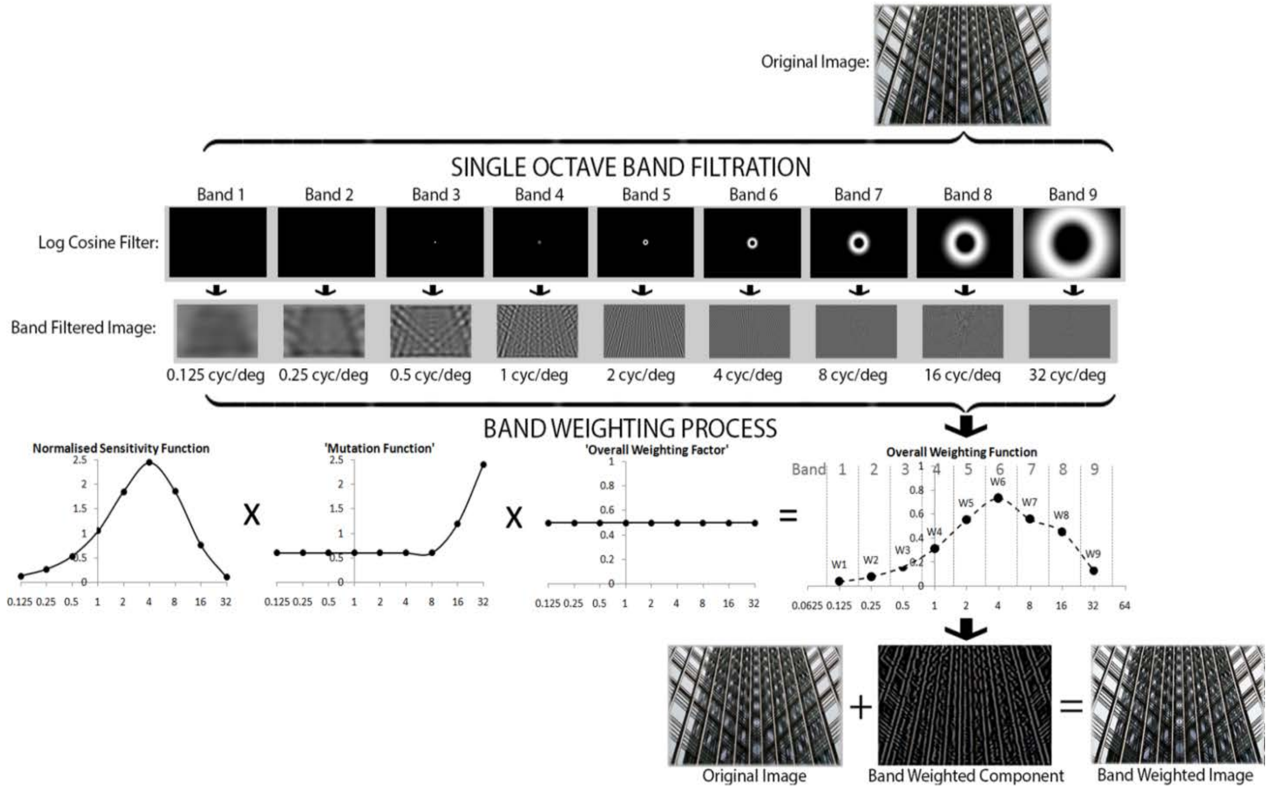


Figure 3. The proposed additive band weighting process

## 3. IMAGE CAPTURE AND DEVICE CHARACTERISATION

### 3.1 Test image characteristics

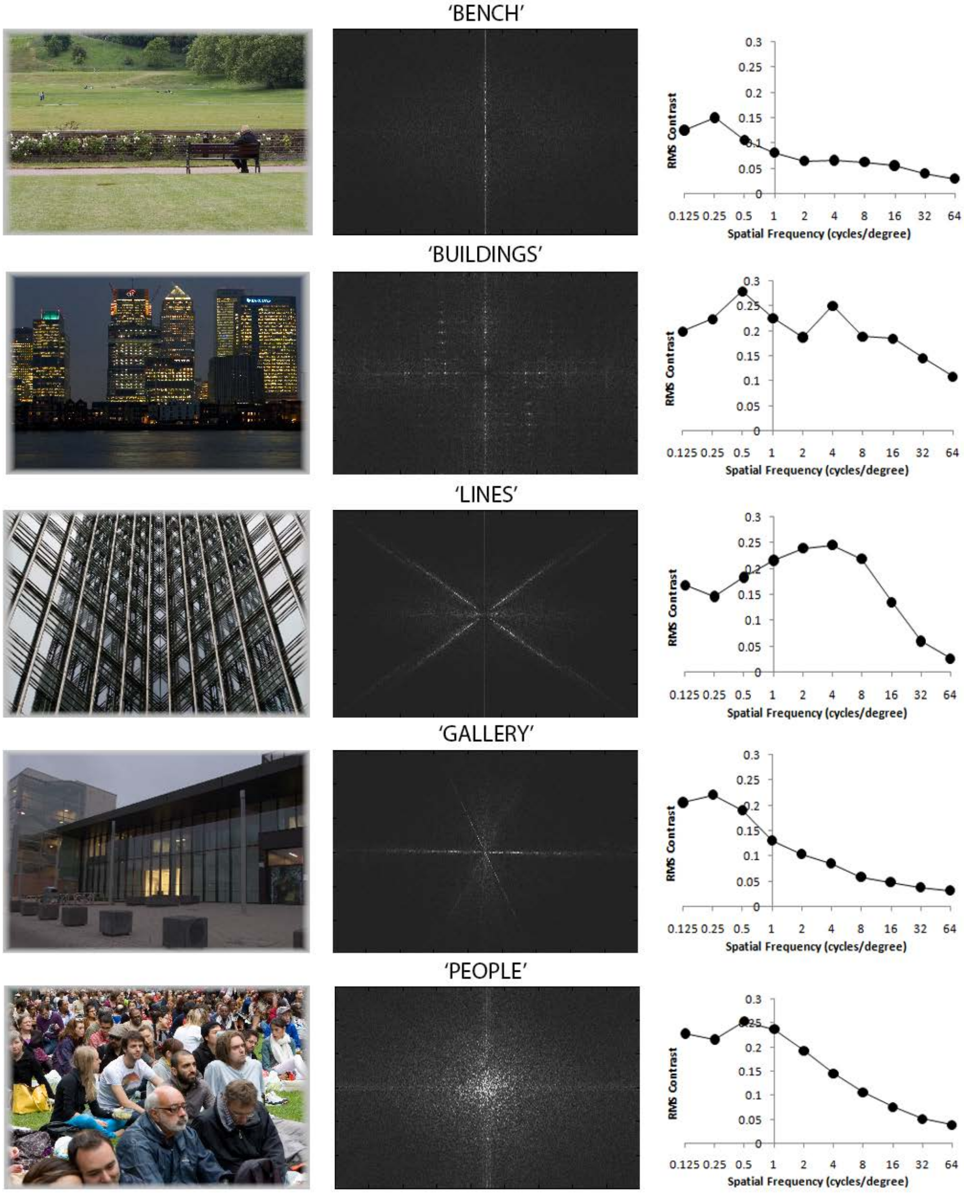


Figure 4. Test images (left), their Fourier spectra (centre) and band contrast spectra (right)

Test images were captured with a Canon EOS 5D DSLR and a professional quality 50mm lens, set to auto white balance, sRGB color space, ISO 100 and lens aperture of f/8. They were stored uncompressed as .png files. Five images were selected, including a range of natural contrast levels (Figure 4). They were cropped centrally to 1794 x 1196 pixels, with their edges faded to a pixel value of 180 across all RGB channels, which reduced wraparound-errors whilst preserving computational efficiency. The selected images varied in subject content, band contrast spectra, Fourier spectra and spatial structure. Images approaching the limits of the camera's dynamic range were avoided. This avoided clipping caused by channel overflow, resulting from removal of destructive interference in the luminance channel, when bands were reduced in contrast or removed from the image altogether.

### 3.2 System characterization

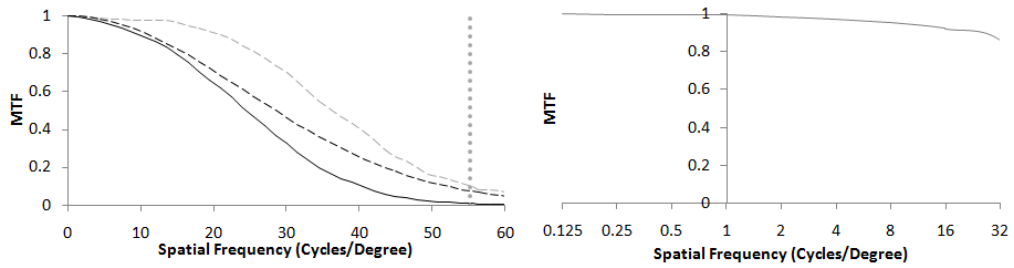


Figure 5. Left: Comparison of the MTF of the Camera-Display system (grey dashed), the Eye's optical MTF (black dashed), a combined Camera-Display-Eye MTF (black continuous), and the Nyquist limit of the camera-display system (grey dotted). Right: Display MTF at 1.97m distance.

The combined camera-display MTF remains above the optical MTF of the eye (modeled according to Barten [(5)]) (Figure 5), indicating that the imaging system is capable of reproducing all frequencies that the HVS is capable of receiving, under the test conditions. The former was calculated according to ISO 12233 [(28)] at the observation distance of 1.97m. At this viewing distance, the display MTF remains close to 1 across all visible frequencies, dropping to a minimum of 0.86 at 32 cycles/degree, meaning spatial contrast reproduction non-linearity is at a maximum of approximately 15%. The capture device OECF was calculated according to ISO 14524 [(29)], and the EOCF of the EIZO CG-245w 24" display, which was calibrated to sRGB conditions, with white point luminance set to 120 cd/m$^2$. The combined camera-display gamma was nearly 1.00 across the most linear section, and the display gamma was 2.164 between pixel values of 45 and 255, with an $R^2$ value of 0.999, indicating good display tone reproduction linearity and accuracy to sRGB standards. CIE u' v' chromaticity diagrams of color output also showed close approximation to intended sRGB gamut. CIE ΔE color differences between a measured and a model color output GOG model [(30)], at maximum channel output, were under 4 units for the B and G channel, and approximately 2 units for the R and combined RGB channels. These color reproduction errors were not significant. Test image band contrast was not adjusted to compensate for spatial contrast reproduction non-linearity in the display (represented by the display MTF, Figure 5), and the gamma of the test images was not adjusted to compensate for the display's tone reproduction non-linearity, or inaccuracy from the sRGB GOG model. Instead, our final weighting-functions (Figure 10) take the spatial display non-linearity into account. This was necessary, because any numerical band weighting applied to image pixels before display, would be affected by the display's spatial contrast reproduction characteristics, which vary across the frequency spectrum.

## 4. MODELING AND MUTATION OF SENSITIVITY FUNCTIONS

### 4.1 Modeling of sensitivity and discrimination functions

iCSFs, cCSFs and cVPFs were calculated according to Triantaphillidou et al [(12)]. This required mean overall display luminances to be calculated for each image, accounting for the effect of the neutral background of pixel value 180 across the R, G and B channels, which the images would be displayed upon. A Crozier value of 3.0 was also used in the modeling process, as recommended by Barten [(5)]. cCSF and cVPF modeling, required RMS band contrast data, resulting in further adaptation across test images (See Figures 1 and 8). Contrast spectra used in the modeling of the cCSF and cVPF did not account for the display MTF, although this would have had a maximum effect of approximately 15%, at 32 cycles/degree (Figure 5). cCSF and cVPF models also required K values [(12)]. K values of between 0.1 and 0.07 were selected after comparison with Triantaphillidou et al. observer data [(12)], for images where observation data were available. A mean K value was selected for images with no observation data. At this stage, a 'constant' normalized function was also created of value 1, across all frequencies. When passed through the same mutation process as the sensitivity functions, this function resulted in band weightings that were identical to the mutation functions themselves.

### 4.2 Sensitivity function mutation

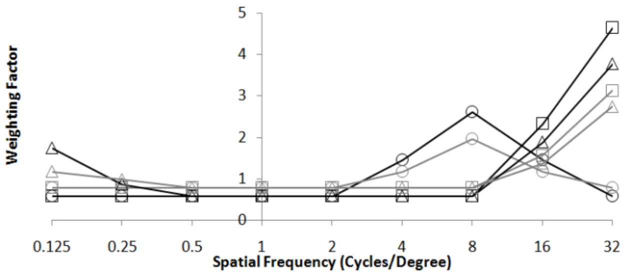


Figure 6. Normalized mutation functions: MHF-S (grey circles), MHF-H (black circles), HF-S (grey squares), HF-H (black squares), HFLF-S (grey triangles), HFLF-H (black triangles).

Each mutation function preserves the spectral power of a 'constant' function, since all mutations have a mean weighting of 1. Three varieties of mutation function are provided at a slight (S) or heavy (H) 'intensity level', focusing upon the following frequencies: mid-high frequencies centered at 8 cycles/degree (MHF-S, MHF-H), high frequencies centered at 32 cycles/degree (HF-S, HF-H) and both high and low frequencies together, at 32 and 0.125 cycles/degree respectively (HFLF-S, HFLF-H). Figure 6 shows all mutation functions, with different focal points and intensities of high frequency boosting.

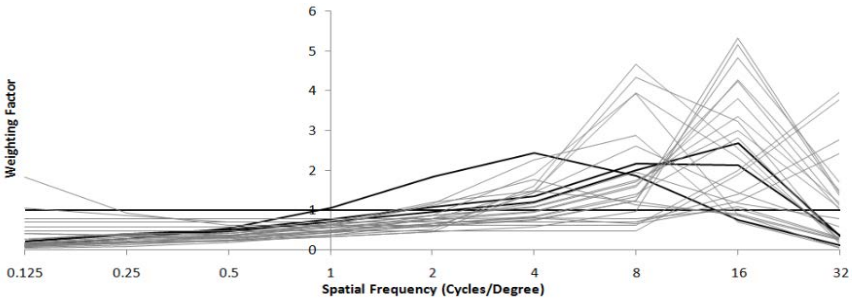


Figure 7. All 4 pure functions (black), and 24 mutated functions (grey) for the 'Bench' image, displaying function spread around higher frequencies.

Multiplication of the iCSF, cCSF and cVPF and 'constant' functions, with 6 different mutation functions, produced a total of 24 mutated functions with large high-frequency spread, as shown in Figure 7 for the Bench image. The non-mutated sensitivity functions are referred to as 'pure', and are provided for comparison.

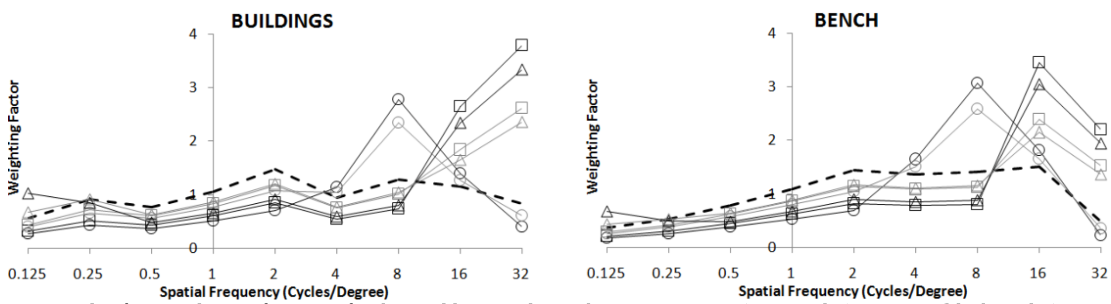


Figure 8. Example of mutated cCSF functions for the 'Buildings' and 'Bench' image: MHF-S (grey circles), MHF-H (black circles), HF-S (grey squares), HF-H (black squares), HFLF-S (grey triangles), HFLF-H (black triangles), PURE (dashed).

The mutated cCSF (Figure 8) and cVPF showed significant variation between scenes, forming a basic adaptive scene-dependent system. These adaptations directly relate to the contextual sensitivity of the HVS to the test images, as described in Section 2.1.

### 4.3 Overall weighting factor

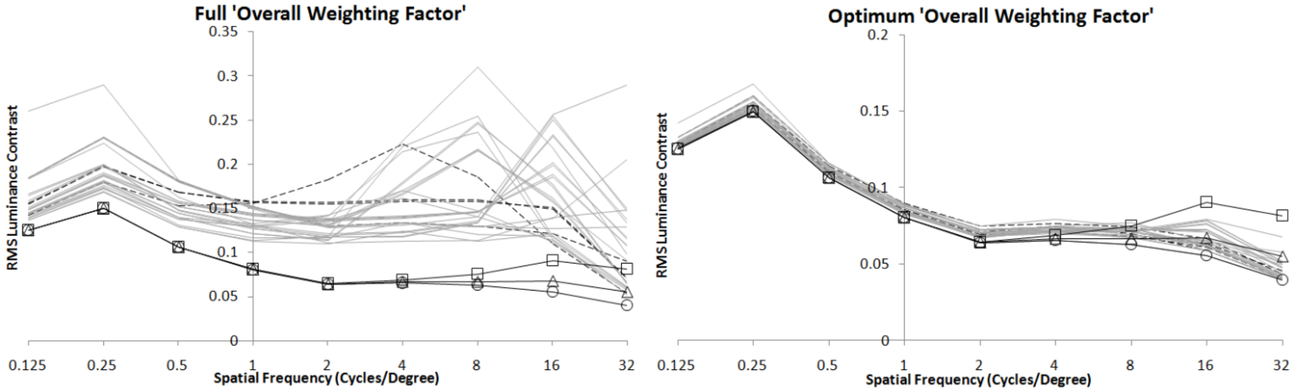


Figure 9. Band contrast spectra, displaying the effects of overall-weighting-factor, for the 'Bench' image; Original image (circles), 'Sharpen' filtered image (triangles), 'Sharpen-More' filtered image (squares), pure functions (dashed), mutated functions (grey lines)

The overall-weighting-factor provides constant weighting across all frequencies, at 1, 1/2, 1/4, 1/8 and 1/16th of the full weighting. Due to time constraints, only one (trained) observer was used to select the optimum overall-weighting-factor for each sensitivity and mutation function combination (Figure 9). Later verification tests indicated strong correlations between this initial observer's data, and data from several other observers, across a large random selection of test image, sensitivity function and mutation function combinations.

### 4.4 Combination into a final weighting-function

The final contrast weighting-function, was obtained by multiplying the sensitivity function, mutation function and overall-weighting-factor. The 9 band-limited images, were multiplied by this contrast weighting-function at their centre-frequency, producing a band weighted frequency component, which was added to the original image's contrast spectrum as shown in Figure 3.

## 5. PSYCHOPHYSICAL TESTING AND ANALYSIS OF RESULTS

### 5.1 Psychophysical test setup, and processing of results

Psychophysical tests, were of a side-by-side, two-alternative, forced-choice type. Images in each test pair were cropped to 800 x 800 pixels after all other image processing had been completed. They were then presented in a dark environment, on a neutral grey background with R, G and B pixel values of 180, at a fixed distance of 1.97m. The dark surround in our test setup is expected to decrease observed contrast of any images presented, relative to sRGB conditions, due to contrast adaptation in the eye [3]. Nine experienced observers participated, each with normal or corrected vision. They were asked to select the image they judged to be of highest quality. Each test contained all contrast-weighted images, Photoshop's Sharpen and Sharpen-More filtered versions and the original image. Sessions were restricted to 40 minutes to avoid observer fatigue. Probability data was converted to interval scaled Z scores using a self-designed automated system in Matlab, with extreme probabilities set to 0.95 and 0.05.

### 5.2 Analysis of image quality results

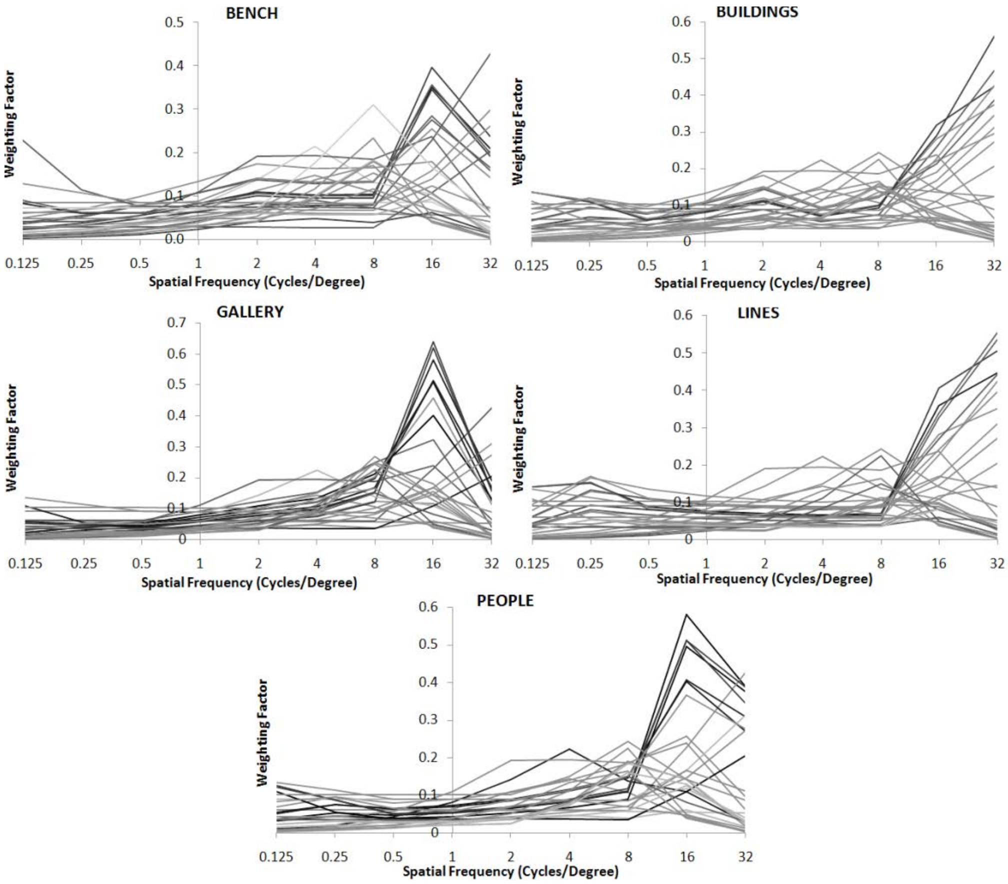


Figure 10. Contrast weighting-functions for each test image, indicating the level of observed image quality, the darker the lines, the higher the quality.

All contrast weighted images were of higher quality than the original image, regardless of which sensitivity or mutation functions were used in their production. Many types of weighting outperformed Photoshop's Sharpen and Sharpen-More functions, with greater consistency of quality across the test image set, with mutations of the cCSF and cVPF showing strongest overall performance. High-frequency boosted mutations (HF-S and HF-H and HFLF-H) of the cCSF and cVPF consistently provided highest quality. Pure cCSF and cVPF weighted images slightly outperformed the pure 'constant' and iCSF functions, although standard error limits make these differences inconclusive.

The darkest lines in Figure 10 are clearly grouped, and represent the weighting-functions which provided highest image quality, which were most commonly high-frequency boosted versions of the cCSF and cVPF. Three out of five test images peaked at 16 cycles/degree, which is the peak frequency for sharpness enhancement for our experimental conditions, according to Bouzit and MacDonald's observations (see Section 2.2) [18]. The most successful weighting-functions were more effective with higher 'overall-weighting-factor', and were considerably more consistent in their optimization of quality, across the image set. The contrast weighting-functions, displayed in Figure 10, account for the MTF of the display. This means they describe the luminance contrast changes caused by our weighting process, at the point where the signal reaches the eye of the observer. Performing the reverse of this process with a new display MTF, would allow this experiment to be repeated using other display systems, or at different display distances.

### 5.3 Preliminary tests on the relationship between sharpness, naturalness and quality.

A final short investigation into the effects of weighting-functions upon sharpness and naturalness, involved the same setup and image processing as the image quality tests. Tests were repeated three times, by the same trained observer who selected the overall weighting factor for each image.

High frequency boosted mutations of the cCSF and cVPF, also provided highest sharpness of all weighting-functions tested. They slightly outperformed Photoshop's Sharpen filter, whilst also enhancing image naturalness far beyond the mean level. Their sharpening capabilities were outperformed by the Photoshop's Sharpen-More filter, although the latter provided the poorest naturalness scores of all.

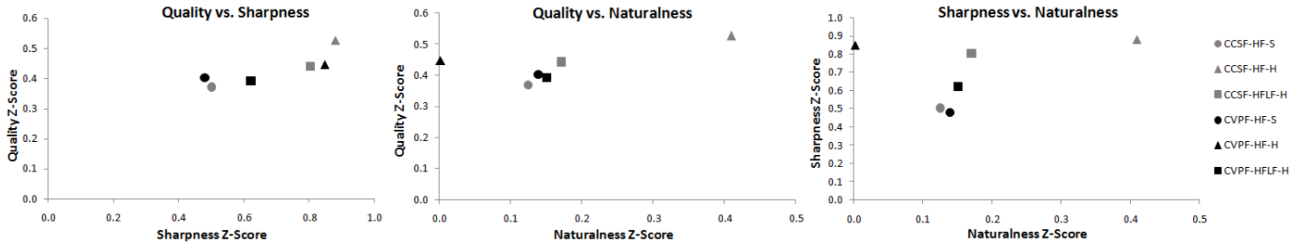


Figure 11. Correlations of the most successful weighting-functions for quality, sharpness and naturalness.

Figure 11 shows HF-S and HF-H and HFLF-H mutations of the cCSF and cVPF in the top right hand quadrant of every correlation plot, suggesting that the highest quality images should show some naturalness.

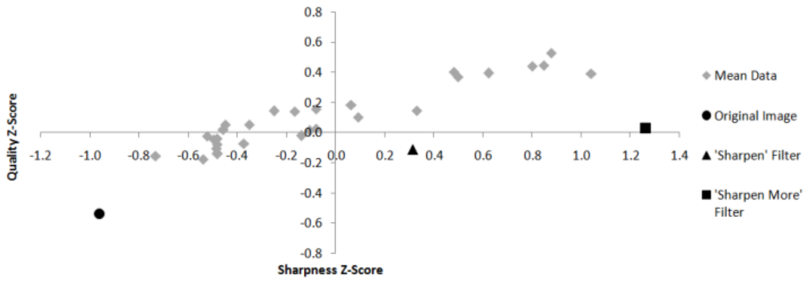


Figure 12. Quality vs. sharpness correlation for all tested weighting-functions.

Strong correlations were observed between quality and sharpness, across all data (Figure 12). This data occupies a linear strip of 0.25 standard deviations width, which shows no signs of tailing off. Mean data values for the Photoshop Sharpen and Sharpen-More filtered versions, and the original image, are located outside this 0.25 standard deviation region, in regions of lower quality.

# 6. DISCUSSION

## 6.1 Conclusions

In this paper, a method of controlled function mutation, produced twenty-four weighting-functions with many high-frequency boosted shape variations, which directly related to three HVS sensitivity models and a constant function. These weighting-functions were cascaded with the luminance contrast spectrum to produce a band-weighted frequency component, to be added to the original image. This 'additive' system permitted any function to be applied with no losses in contrast, and was based upon high-pass filter and USM application methods. Nine experienced observers performed psychophysical evaluations of image quality, involving all contrast weighted images, the original image, and images filtered with Photoshop's Sharpen and Sharpen-More filters; a shorter investigation into image sharpness and naturalness was also performed. Test images ranged in subject content, band contrast spectra, Fourier spectra and spatial structure.

Weighting-functions providing the highest quality, showed strong similarity when viewed on the same axes for each image, and achieved greatest quality at a heavier overall weighting than other functions. They peaked at 16 or 32 cycles/degree, representing the upper range of HVS spatial sensitivity. Once mutated to boost the higher frequencies, suprathreshold contrast detection (cCSF) and discrimination (cVPF) functions (which showed greatest adaptation to variations in test image spectra), consistently provided the highest quality across our image set, also providing the highest sharpness and higher than average naturalness. The role of suprathreshold detection and discrimination functions in image quality models, will be explored further in our research.

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**Removed from report, but included for reference:**

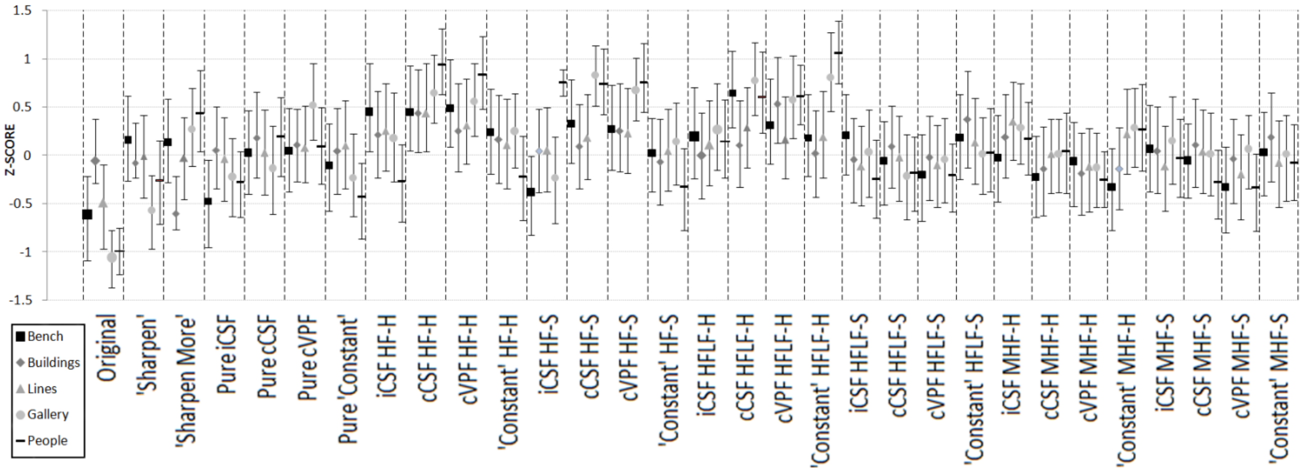


Figure ?. Observed quality of all tested weighting-functions

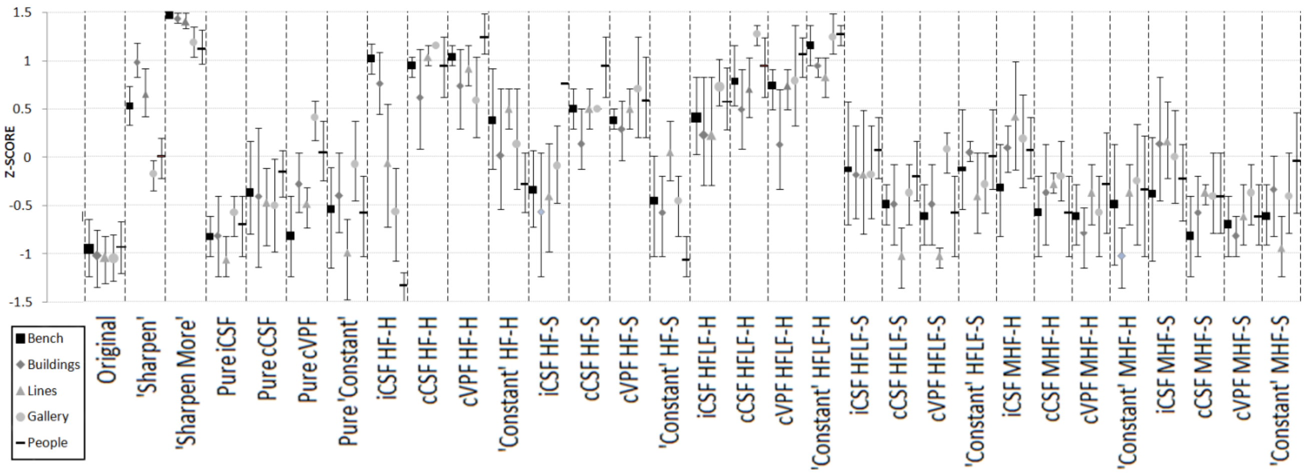


Figure ?. Observed sharpness of all tested weighting-functions

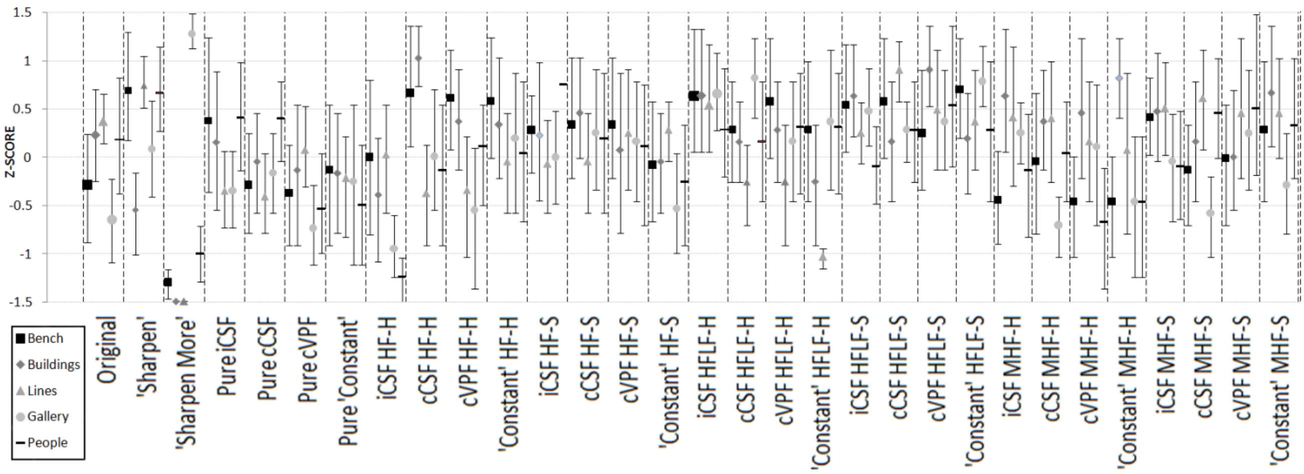


Figure ?. Observed naturalness of all tested weighting-functions