

Lightness Constancy in Edge Detection: A Simple Approach using Luminance Ratios

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Abstract—Reliable edge detection is of utmost importance to many sophisticated computer vision methods and has been historically computed using luminance differences, which are quite sensitive to changes in illumination. It is argued here that using luminance ratios for edge detection in computer vision, rather than luminance differences, results in more robust edge information with respect to changes in illumination, which is in line with theoretical models for the lightness constancy observed in human visual perception. In order to test this hypothesis, a simple technique that converts luminance differences into luminance ratios with minimal effort is proposed. Experiments regarding edge detection and image segmentation under simulated changes in illumination show promising results for the luminance ratio approach.

I. INTRODUCTION

Adaptation to different illumination conditions is a fundamental trait of the human visual system, which is also extremely desirable to computer vision systems that aim at extracting robust environmental descriptions from images regardless of illumination changes. This particular trait is known as perceptual constancy and consists in perceiving the properties of visual objects, which are usually constant over different viewing conditions, rather than the properties of their projected images, which are variable over different viewing conditions [1]. Figure 1 illustrates the concept of achromatic lightness constancy, which is the main subject of this paper.

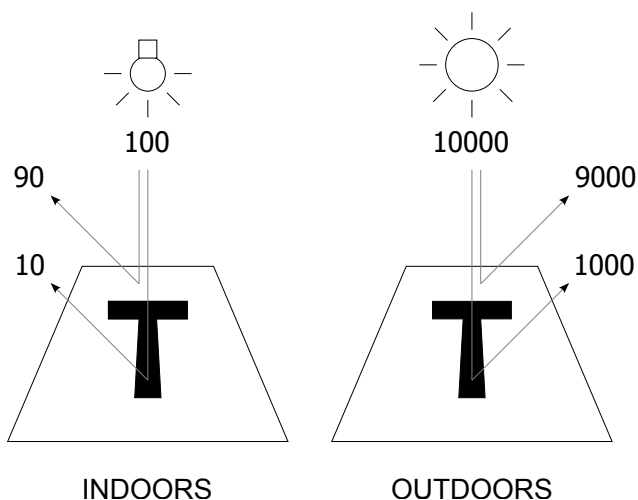


Fig. 1. Achromatic lightness constancy: human perception of black ink on white paper is the same under very different illumination levels (adapted from [1]).

Human perception of black ink on white paper is the same despite the amount of illumination in the environment. However, the example in Fig. 1 shows that the amount of reflected light outdoors is a hundred times larger than indoors – what remains constant in both illumination conditions is the relative amount of reflected light for dark and light regions of the image. According to the theory of lightness constancy of Hans Wallach [2], *luminance ratios* are what determine perceived lightness and contrast – one can notice that the luminance ratio is the same (9:1) in both illumination conditions depicted in Fig. 1.

In computer vision, a key concept regards edge detection – measurements of local contrast that allow the segmentation of image regions according to the reflected luminance. Edge detection in computer vision systems has been historically estimated by difference operators – for example, convolution with Prewitt or Sobel masks – which approximate luminance gradients. This technique, whose results are rather sensitive to changes in illumination, dates back to an age in which computing power was very limited in terms of mathematical functions available for practical implementations. With the increased computing power that became largely available and now allows practical implementations using more sophisticated mathematical functions and also more advanced numerical representations, a paradigm shift towards edge detection using luminance ratios may be in order. The hypothesis is that luminance ratios are able to provide edge information that is more robust to illumination changes than luminance differences. In this context, a quantitative performance comparison of edge detection using both luminance differences and luminance ratios is made here for simulated changes in illumination.

The remainder of this paper is structured as follows. In Section II, a simple mathematical property that conveniently converts luminance differences into luminance ratios is described. Section III presents the experimental setup used to test the ratio-based edge detection and compare it to the difference-based approach. The experimental results obtained are presented and discussed in Section IV, and finally, in Section V, conclusions are drawn and future work outlined.

II. LUMINANCE RATIOS FROM LUMINANCE DIFFERENCES

A vast number of computer vision methods rely on information extracted from gray level images using luminance differences, which are quite simple to compute and provide effective results if illumination conditions are kept reasonably constant. The purpose here is to establish a method to convert luminance differences into luminance ratios without resorting

to radical changes in existing edge detection techniques, so that more sophisticated methods that rely on them can benefit almost immediately from edge information that is more robust to changes in illumination.

A very simple way of mapping ratios to differences consists in using the well-known property of logarithms expressed in Eq. 1:

$$\log_b \left(\frac{p}{q} \right) = \log_b(p) - \log_b(q). \quad (1)$$

Equation 2 shows a convenient way of mapping eight-bit gray levels to a normalised logarithmic scale, when $b = 256$ is used:

$$g(x, y) = \log_{256}[f(x, y) + 1], \quad (2)$$

where $g(x, y)$ is the logarithmic mapping in the range $[0, 1]$ of gray level $f(x, y)$. The inverse mapping, from normalised logarithmic values back to the linear scale in the range $[0, 255]$, can be done by using Eq. 3:

$$f(x, y) = 256^{g(x, y)} - 1. \quad (3)$$

Therefore, performing ratio-based edge detection merely consists in three steps: (1) mapping the original input image to the normalised logarithmic scale using Eq. 2; (2) performing conventional difference-based edge detection with no alterations; (3) optionally mapping the resulting edge image (magnitude only) back to the linear scale using Eq. 3. It is worth noting that ratio-based edge detection preserves the direction of local image gradients to great extent. Floating point numerical representations must be used in all steps in order to ensure accuracy of results.

III. EXPERIMENTAL SETUP

In order to test the proposed ratio-based edge detection method and make comparisons to the existing difference-based method, experiments were designed in which image intensities were artificially manipulated. A gray level version of the Lena image with 256×256 pixels in size was used as input to both techniques, with synthetic changes in illumination obtained by applying increasing attenuation factors (from 0% to 100% in steps of 5%) to the pixels of the image. Two scenarios were investigated: (1) uniform attenuation factors were applied globally to the input image; (2) varying attenuation factors were applied locally to the input image, following v-shaped profiles, as shown in Fig. 2.

The v-shaped attenuation profiles used in the experiments have maximum attenuation in the middle of the horizontal dimension of the input image. Figure 2 shows two examples of such attenuation profiles, one of them with maximum attenuation of 50% (blue line) and the other with maximum attenuation of 100% (red line). This approach is used to investigate the performance behaviour of both edge detection approaches when nonuniform illumination profiles affect the input image.

The expected outcome of these experiments is that ratio-based (logarithmic gradient) edges are less sensitive to changes in illumination than their difference-based (linear gradient) counterparts.

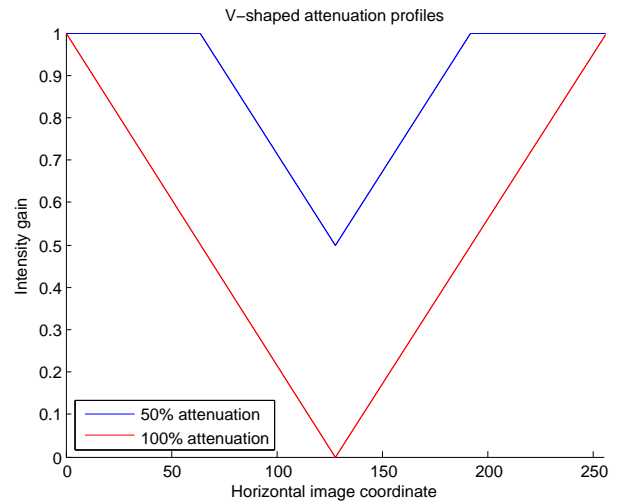


Fig. 2. V-shaped attenuation profiles: intensity attenuation is a function of the horizontal coordinate of pixels in the original input image. The blue line corresponds to a maximum attenuation of 50% while the red line corresponds to a maximum attenuation of 100% in the middle of the image.

Figure 3 shows examples of the resulting input images after the synthetic illumination changes described before. The original Lena image is shown in Fig. 3a, whereas Fig. 3b shows its uniformly attenuated version at 50%. Figures 3c and 3d show the resulting input images after the v-shaped attenuation profiles at 50% and 100% (see Fig. 2) were applied, respectively, where progressively dark vertical lines in the middle of the images can be noticed.

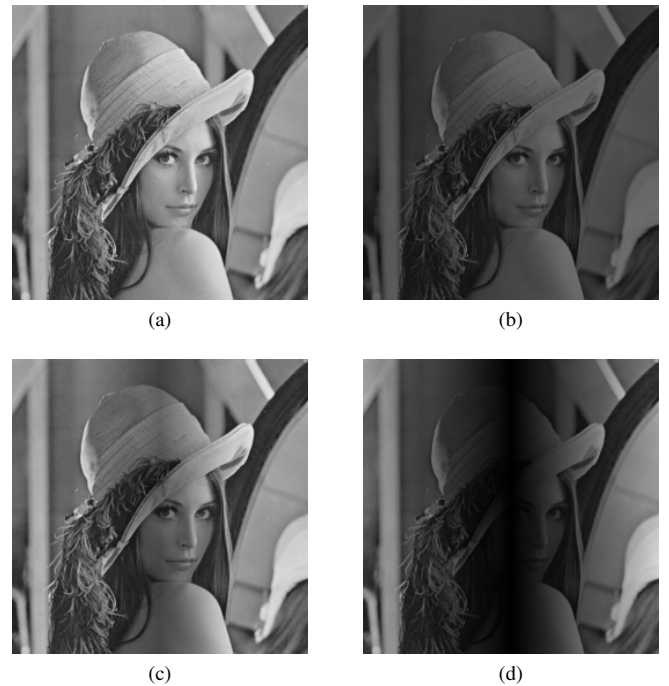


Fig. 3. Input images: (a) original Lena image; (b) 50% uniform intensity attenuation; (c) 50% v-shaped intensity attenuation profile (blue line in Fig. 2); (d) 100% v-shaped intensity attenuation profile (red line in Fig. 2).

A first experiment was conducted, in which the original Lena image and its attenuated versions were used as inputs to the Sobel edge detection method [3], both using the conventional difference-based approach (linear gradient) and the proposed ratio-based approach (logarithmic gradient). In order to assess the influence of changes in luminance, the edge results for the original image were used as a baseline for computing the root mean square (RMS) error of edge results for each attenuated image.

The RMS error for edge magnitudes was computed using:

$$me_{RMS} = \sqrt{\frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} [m_a(x, y) - m_o(x, y)]^2}, \quad (4)$$

where M is the horizontal image dimension, N is the vertical image dimension, $m_a(x, y)$ are the resulting edge magnitudes for the attenuated image and $m_o(x, y)$ are the edge magnitudes for the original image. The RMS error for edge magnitudes was normalised using the extreme case in which no edges can be detected (100% uniform attenuation):

$$me_{RMS,max} = \sqrt{\frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} m_o(x, y)^2}. \quad (5)$$

The RMS error for edge directions was computed using a modified version of Eq. 4:

$$de_{RMS} = \sqrt{\frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} [\text{angdif}(o_a(x, y), o_o(x, y))]^2}, \quad (6)$$

where $\text{angdif}(\cdot)$ is a function that computes angular differences considering their periodicity, $o_a(x, y)$ are the resulting edge directions for the attenuated image and $o_o(x, y)$ are the edge directions for the original image, always having the difference-based edge directions as baseline. The RMS error for edge directions was normalised using the extreme case in which all directions are opposite to the baseline reference:

$$de_{RMS,max} = \sqrt{\frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \pi^2}. \quad (7)$$

In order to minimise the effect of noise, directions corresponding to weak edge responses (less than 10% of the maximum edge magnitude in the entire image) are discarded when computing the RMS error for edge directions.

Finally, an additional experiment was conducted using the same set of images as inputs to the blob colouring segmentation algorithm [4], which is based in luminance differences between adjacent pixels and is therefore known to be sensitive to changes in illumination, which can cause flooding effects that merge adjacent regions. A preliminary quantitative assessment of how much changes in luminance affect blob colouring segmentation results was done by counting the number of segmented regions when using both concepts of linear and logarithmic gradients.

IV. EXPERIMENTAL RESULTS

A. Sobel Edge Detection

The experiments regarding the impact of changes in illumination on Sobel edge detection [3] were initially conducted using uniform luminance attenuation (see Figs. 3a and 3b), in which resulting edge magnitudes and directions were assessed for increasing attenuation factors.

Fig. 4 shows the normalised RMS error for edge magnitudes as a function of uniform intensity attenuation for linear and logarithmic gradient approaches.

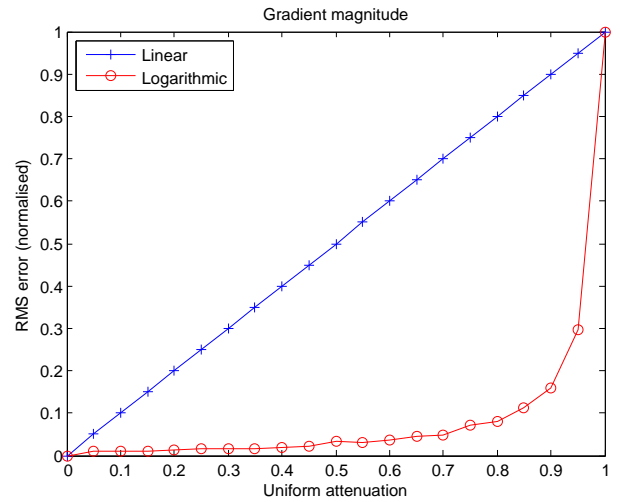


Fig. 4. Normalised RMS error for gradient magnitudes as a function of uniform intensity attenuation: linear gradient magnitudes (blue line) are heavily affected by changes in luminance, whereas logarithmic gradient magnitudes (red line) are much more robust – 80% intensity attenuation results in less than 10% of the maximum RMS error when using the logarithmic gradient.

As can be clearly noticed in Fig. 4, the normalised RMS error for linear gradient magnitudes increases linearly with uniform luminance attenuation, indicating that the conventional difference-based edge detection performance is heavily affected by changes in illumination. On the other hand, the normalised RMS error for logarithmic gradient magnitudes is less affected by changes in illumination, as predicted by Wallach’s lightness constancy theory [2] – uniform attenuation factors as high as 80% result in less than 10% of the maximum expected RMS error for ratio-based edge magnitudes.

Figure 5 shows that the normalised RMS error for edge directions as a function of uniform changes in illumination is not critical for both linear and logarithmic gradient approaches, but the results indicate that the logarithmic gradient approach yields a small directional offset in comparison to the reference baseline, given by the conventional linear gradient directions of the original input image. However, Fig. 5 also indicates that logarithmic gradient directions are much more stable to changes in luminance than their linear gradient counterparts, a characteristic that is desirable to gradient-based descriptors often used in state-of-the-art object recognition methods such as SIFT [5], [6] and SURF [7].

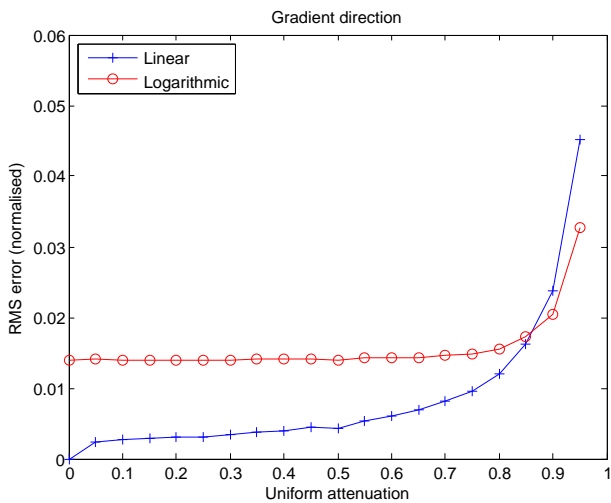


Fig. 5. Normalised RMS error for gradient directions as a function of uniform intensity attenuation: despite presenting a small average angular offset, logarithmic gradient directions (red line) are more stable to changes in luminance when compared to linear gradient directions (blue line).

Following the experiments regarding the impact of uniform changes in illumination on Sobel edge detection, additional experiments regarding nonuniform *gradual* changes in luminance were conducted. In these experiments, the resulting edge magnitudes and directions were assessed for increasing maximum attenuation factors in v-shaped attenuation profiles (see Figs. 2, 3c and 3d).

The normalised RMS error for edge magnitudes as a function of nonuniform intensity attenuation for linear (difference-based) and logarithmic (ratio-based) gradient approaches is shown in Fig. 6.

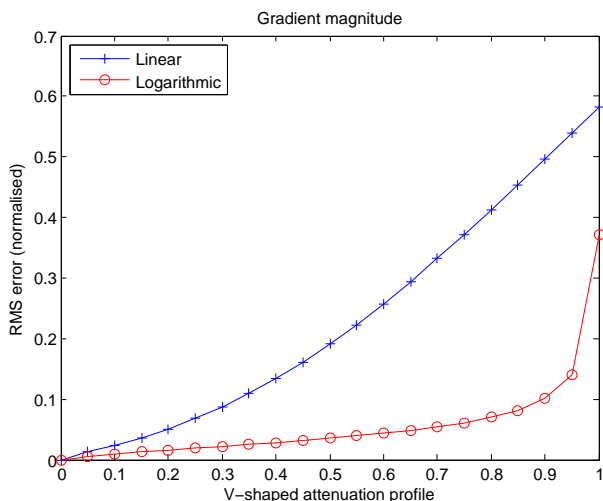


Fig. 6. Normalised RMS error for gradient magnitudes as a function of nonuniform intensity attenuation (v-shaped attenuation profile): as in the case of uniform intensity attenuation, linear gradient magnitudes (blue line) are much more affected by changes in luminance than logarithmic gradient magnitudes (red line).

It can be noticed in Fig. 6 that conventional linear gradient magnitudes are much more affected by nonuniform changes in illumination than logarithmic gradient magnitudes, as expected. Figure 7 visually illustrates the effects of the v-shaped attenuation profiles (100% maximum attenuation) on edge detection using both linear and logarithmic approaches.



Fig. 7. Sobel edge detection results: (a) linear gradient magnitude (original input image); (b) logarithmic gradient magnitude (original input image); (c) linear gradient magnitude (100% v-shaped attenuation profile); (d) logarithmic gradient magnitude (100% v-shaped attenuation profile). The resulting linear gradient magnitude is much more affected than the resulting logarithmic gradient magnitude when comparing (c) and (d). All edge images were complemented for visualisation purposes, but absolute magnitudes were kept unchanged in order to allow fair visual comparisons between results.

Although stronger edge responses can be observed in the linear gradient results for the original input image (Fig. 7a), linear edge responses are somewhat noisy and clearly fade away when the image is affected by nonuniform attenuation, especially in the middle of the horizontal dimension (Fig. 7c). In the case of logarithmic gradient results for the original input image (Fig. 7b), edge responses are not as strong as the ones observed in the linear case. However, logarithmic edge responses are less noisy and do not fade away when the input image is affected (Fig. 7d) – except from some vertical artifacts that appear in the middle of the horizontal dimension as a result of extreme intensity attenuation in that region (100%), overall logarithmic edge responses are reasonably stable to nonuniform changes in luminance.

The impact of nonuniform changes in luminance on edge directions is shown in Fig. 8, where it can be noticed that difference-based edge directions are more severely affected by nonuniform changes in illumination – notice that the normalised RMS error for linear gradient directions rises at higher rates in comparison to Fig. 5. On the other hand, ratio-based edge directions show stable behaviour even in the presence of gradual changes in illumination.

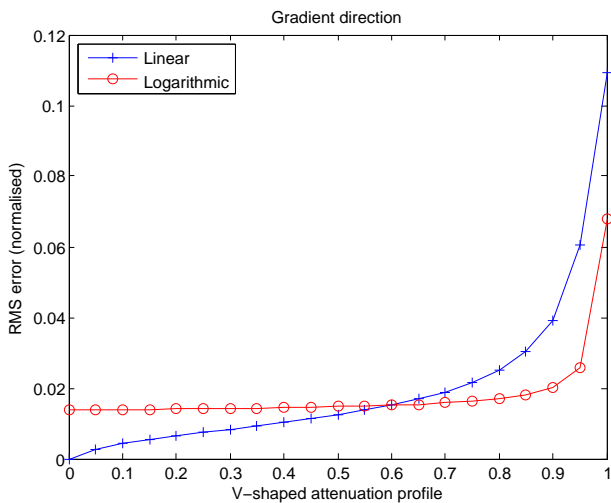


Fig. 8. Normalised RMS error for gradient directions as a function of nonuniform intensity attenuation (v-shaped attenuation profile): logarithmic gradient directions (red line) are more stable to changes in luminance than linear gradient directions (blue line), which are more severely affected by nonuniform than uniform intensity changes (compare to Fig. 5).

B. Blob Colouring Segmentation

The final experiment was conducted in the context of the blob colouring algorithm, which is a segmentation method that grows regions based on the contrast between adjacent pixels [4]. The objective of this last experiment was to assess how blob colouring segmentation results are affected by changes in illumination, when difference-based or ratio-based contrast estimation are used. For that, the number of resulting regions at the end of the segmentation process was used as a direct quantitative measurement of the impact of uniform and nonuniform changes in luminance. The threshold used for the difference-based approach was 7% of the maximum possible contrast magnitude and the threshold used for the ratio-based approach was 3.3% – these values were chosen to result in approximately the same number of regions for the original image.

Figure 9 shows the number of regions resulting from the blob colouring process as a function of uniform intensity attenuation for both difference-based and ratio-based contrast. It can be noticed that the number of regions for the linear approach are radically affected by luminance attenuation – originally separated regions are gradually merged because of the resulting difference-based contrast attenuation. On the other hand, the number of regions for the logarithmic approach is reasonably stable for a wide range of attenuation factors. The unexpected peak observed in the number of regions for the logarithmic approach is explained by truncation errors in small intensity values that happen as part of the simulation of changes in illumination.

The number of regions resulting from the blob colouring process when nonuniform luminance attenuation is applied to the original input image is shown in Fig. 10, where once more it can be noticed that the ratio-based approach is still much more resilient to changes in luminance when compared to the conventional difference-based approach.

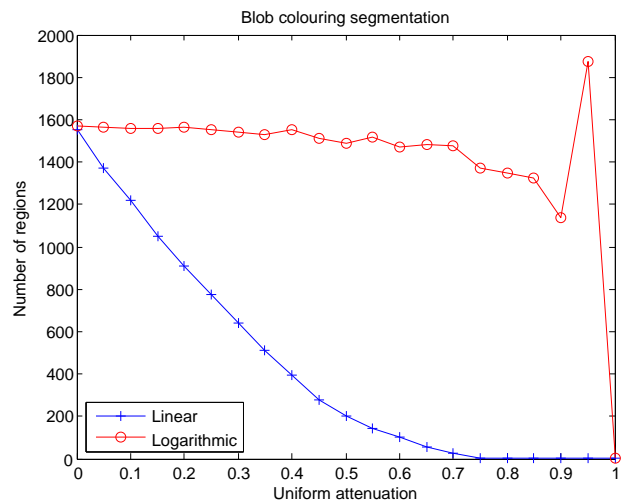


Fig. 9. Number of regions resulting from the blob colouring process as a function of uniform intensity attenuation: the number of segmented regions for the difference-based (linear) contrast decreases radically with increasing uniform attenuation factors, as a result of originally separated regions being merged, whereas the number of segmented regions for the ratio-based (logarithmic) contrast is reasonably stable (the unexpected peak at 95% attenuation is due to truncation errors in small intensity values).

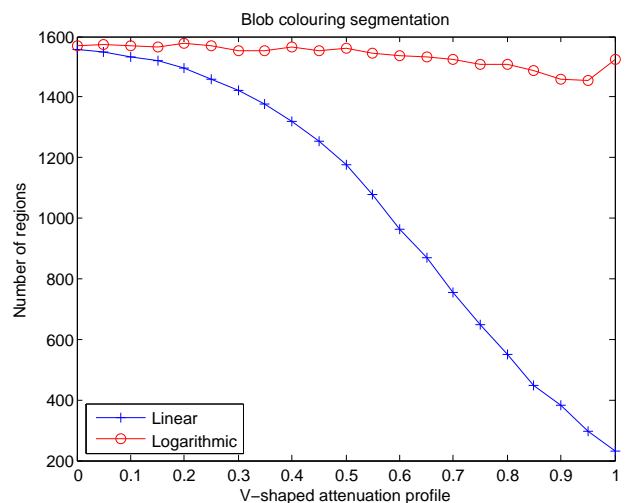


Fig. 10. Number of regions resulting from the blob colouring process as a function of nonuniform intensity attenuation (v-shaped attenuation profile): the number of segmented regions for the ratio-based (logarithmic) contrast is much more stable than the number of segmented regions for the difference-based (linear) contrast.

V. CONCLUSION

Wallach's theory of lightness constancy states that human perception of contrast is based on luminance ratios [2], which provide a large degree of invariance to changes in illumination. However, contrast estimations in computer vision are traditionally computed by difference operators [3], which in their turn are quite sensitive to changes in illumination.

In this work, a simple mathematical property was used in order to convert luminance differences into luminance ratios, enabling changes with minimal effort in existing difference-based edge detection algorithms. Despite its simplicity, the proposed method provides edge detection results that are much more stable to changes in illumination and therefore can be of special interest to more versatile computer vision applications.

Preliminary experiments assessing the performance of difference-based and ratio-based gradients indicate that the ratio-based approach is indeed rather robust to simulated changes in luminance in the context of edge detection and image segmentation. Future work includes extending experiments to test the ratio-based edge detection approach using input images acquired in different physical lighting conditions, and also testing this concept in the context of object recognition algorithms such as SIFT [5], [6] and SURF [7].

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