

Local contrast for no-reference colour quality assessment

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Abstract

Image quality assessment plays an important role in various image processing applications. In recent years, some objective image quality metrics correlated with perceived quality measurement have been developed. Two categories of metrics can be distinguished: full-reference and no-reference. Full-reference looks at decrease in image quality from some reference of ideal. No-reference approach attempts to model the judgment of image quality directly, independent of the reference. Unfortunately, the universal image quality model is not on the horizon and empirical models establish on psychophysical experimentation are generally used. In this paper, we present a new algorithm for colour reproduction quality assessment based on human visual system modeling. A local contrast definition [1] is used to assign quality scores. Finally, a good correlation is obtained between human evaluations and our method.

Introduction

Image quality models are known to be multivalued with some visual attributes. In image reproduction, image contrast is commonly defined in terms of tone reproduction curve. Unfortunately, two sets of images having very different white and black points may have very different perceptual contrasts. Image quality can't be established from the tone reproduction curve. Consequently, some empirical models based on psychophysical experimentation are developed to compute the quality perceived regarding the contrast in an image. The more succeeded model uses a simple definition of Lightness-Contrast, Chroma-Contrast and Sharpness-Contrast [2] in Lab colour space. However, the parameter weights in this type of models depend on the set of images used in the human quality assessment. To solve this problem, we proposed a new no-reference algorithm based on a modelisation of the human visual system. Initially, we compute the perceived information on a soft or hard reproduction image. Then, a local contrast definition is used to assign quality scores. Finally, we use a psychophysical experimentation to evaluate the performance of the proposed method.

Method

The first step of our method computes the perceived information from a displayed image by using colour contrast sensitivity function in an opponent colour space. The contrast sensitivity function is probably the most important stage in any HVS model. The output image is filtered by a set of band-pass filters and fan filters like cortex transform [3]. Five spatial frequency bands and five orientations compose the frequency decomposition. The effects of these filters are cascaded to describe the combined radial oriental selectivity of cortical neurons.

The next step computes the local band-limited contrast to assign quality scores. The frequency bands information is converted into some measure of contrast. Generally, Weber or Michelson contrasts are used to compute simple stimuli contrast. In our model, these definitions cannot be used because a real image is not symmetric and

these definitions are global quantities depending on the average luminance of the whole image. We used a modified version of the Peli's definition:

$$LBC_{k,l}(x,y) = \begin{cases} \frac{B_{k,l}(x,y)}{M_{k,l}(x,y) + \sum_{i=0}^{k-1} B_{i,l}} & \forall k = 2 \dots K, l = 1 \dots L \\ \frac{B_{k,l}(x,y)}{M_{k,l}(x,y) + B_0} & \forall k = 1, l = 1 \end{cases}$$

where B_0 is the average of the image defined by the center of Daly frequency decomposition and $M_{k,l}$ depends of the average of the image and can be used to model the frequency and orientation sensitivity of the HVS.

Results and conclusion

To corroborate the perceptual relevance of our metric, we carried out one set of subjective experiments. We ask twenty viewers to evaluate the quality perceived in a set of twelve test images representing the typical images used in multimedia applications. With these images, our database was created by simulating nine tone reproduction curves that can be typically obtained in CRT and LCD screens. The nine simulated images were shown to each observer, on the same screen, for each original image. Observers were asked to provide their perception of quality by grading the nine reproduction curves from the best to the worst.

For our analysis, the grade was then converted linearly into scale 1-9 (1 for the worst and 9 for the best). We computed the mean opinion scores (MOS) and the corresponding 95% confidence intervals. Figure 1 shown the results for two images of the test, representing "Athletes" and "Transports". Same results can be computed for the whole database. Very good fitting is obtained between prediction and MOS (90% of correlation between MOS and prediction).

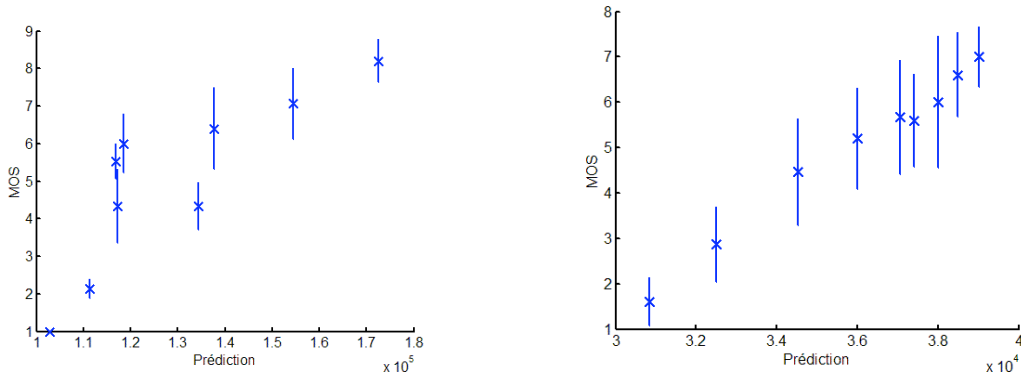


Figure 1. Quality predictions versus mean opinion scores, left: "Athletes", right: "Transports"

These results are encouraging and show a new way of work for image quality measurement without image reference. The use of human visual system modelisation solves the dependency problem of the model parameters from a learning database and allows a generic formulation.

1. E. Peli. Contrast in complex images. Journal of optical society of America, 7(10), October 1990
2. A.J. Calabria and M.D. Fairchild. Perceived image contrast and observer preference II: Empirical modeling of perceived image contrast and observer preference data. Journal of Imaging Science & Technology, 47:494-508, 2003.
3. A. Watson. The cortex transform : Rapid computation of simulated natural images. Computer vision, graphics, and image processing, vol. 39, no. 3:311-327, 1987