Proc. 14th Int. Conf. on Global Research and Education, Inter-Academia 2015
JJAP Conf. Proc. **4** (2016) 011607

Fuzzy Information Measure for Image Quality Improvement

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(Received September 26, 2015)

Digital image processing can often improve the quality of visual sensing of images and real world's scenes however the optimization of the used algorithms is not always an easy task. The suitable parameter settings of the methods often depend on the features of the scenes and may also depend on the aim of the (further) processing. In this paper, a fuzzy information measure is introduced which evaluates the level of information of pictures. The idea behind the technique is that the amount of information in an image is strongly related to the number and complexity of the objects in the image. The primary information about the objects is usually related to their boundaries, i.e. the characteristic, corner and edge, pixels carry the most relevant information about the image content. The measure presented in this paper sums up the fuzzy level of details and this amount is used to scale the qualification and transformation of images. The presented technique can advantageously be built into different image processing algorithms favorably used in Image Quality Improvement and High Dynamic Range Imaging. The qualification measure may also be applied for increasing the color differentiation capability of the human eye and thus, for improving visual sensing.

1. Introduction

Today, research areas related to color vision and image quality improvement (IQI) have become very important. These concern both the light intensity and the color capturing capabilities of the human eye. The reasons behind are that on one hand the color difference perception ability and the minimum distance of which details can be distinguished by the receptors are limited [1]. On the other hand, the human eye is able to capture approximately 4 orders of magnitude of light while the range of light in the real world may span 10 orders of magnitude [2].

In this paper, a new fuzzy information measure (FIM) is introduced which determines the fuzzy amount of information in the image/scene regions. Based on this, locally tuned nonlinear mapping functions can be built to adaptively transform the intensity/color regions of the images/scenes in such a way that the most of the characteristic information can be captured by the light/color receptors of the eye. The method can thus, efficiently be used in information amount based image quality improvement and to increase human visual sensing.

The transformation of the regions basically depends on the amount of visual information in the region. The method assigns bigger spaces to those regions which contain more details taking into account that the human visual sensing is limited in terms of the minimum distance of which details can be distinguished. On the other hand, the technique offers a way to keep parts invariant if their importance makes it necessary. By this, there is a possibility for compressing intensity/color regions where unimportant or sparse information is stored and for extending the important or dense regions. The complexity of the method is low, i.e. allows also real-time processing.

The paper is organized as follows: In Section 2 the new fuzzy information measure is introduced.

Section 3 is devoted to the adaptive FIM based mapping function used in the transformation of the intensity/color regions. In Section 4 FIM based image quality improvement is detailed, while Section 5 briefly presents the concepts of FIM based visual sensing improvement. Finally, Section 6 is devoted to the conclusions.

2. Fuzzy Information Measure Based on the Level of Details

An important question of image processing, image understanding, data storage, information retrieval, and visual sensing is: What carries the information in images or scenes? Although, there are many possible replies to this question, considering statistical elements or the histogram of the luminance values, a simple, new, low complexity one can be the amount of the intensity/color changes in the image or scene. This means that the level of details in an image or view is directly proportional (and thus can be measured and represented) by summing up the intensity/color changes.

Another, more sophisticated approach may also consider the unavoidably present noise which is to be eliminated. This raises another question: What is noise? The main problem of answering this question is that 'noise' is an ill-defined category because noise is usually dependent on the situation and on the intension and objective of the processing. What is characteristic or useful information in one application can be noise in another one. From this follows the idea that, the amount of information in an image/view is strongly related to the number and complexity of the objects in it. Usually, the most characteristics about the objects are their boundaries (which usually can be extracted as edges, representing significant intensity/color changes). The boundary edges of the objects carry the primary information about the object's shape which can serve as base for classification, object recognition, etc. On the other hand, all the other intensity/color changes, texture edges that have been included in the information in the previous approach, can be excluded (thus, decreasing the complexity). According to this concept, image content information can be represented by the characteristic features, like boundary edges. Consequently, the amount of information in the image/scene is proportional to the number of characteristic i.e., boundary edge pixels. Considering an image, the algorithm of the determination of the fuzzy level of details (FLD) carried by the object contours' edges is, as follows:

2.1 Surface Smoothing

Let S_t be the surface describing an image to be processed, i.e. $S_t = \{(x, y, z); z = I(x,y,t)\}$, where variables x and y represent the horizontal and vertical coordinates of the pixels, z stands for the luminance value, which is the function of the pixel coordinates and of time t. Smoothing is performed by image surface deformation. Such a process preserves the main edges (contours) in the image. The surface deformation process satisfies the following differential equation [3]:

$$\frac{\partial I_t}{\partial t} = k\underline{n} \tag{1}$$

where k corresponds to the „speed" of the deformation along the normal direction $\underline{n}$ of the surface S_t. In our case, value k is represented by the mean curvature of the surface at location $[x,y]$, i.e. the speed of the deformation at a point will be the function of the mean curvature at that point. The mean curvature is defined as

$$k = \frac{k_1 + k_2}{2} \tag{2}$$

where k_1 and k_2 stand for the principal curvatures. Starting from (2), the following partial differential equation can be derived (for details, see [4]):

$$k = \frac{(1+I_y^2)I_{xx} - 2I_x I_y I_{xy} + (1+I_x^2)I_{yy}}{2\left(1+I_x^2+I_y^2\right)^{3/2}} . \tag{3}$$

Here I_x, I_y, I_{xx}, I_{xy}, I_{yy} stand for the partial derivatives with respect to the variables indicated as lower indices. Starting from equation (1) the surface at time $t+\Delta t$ (for small Δt) can be calculated, as [3]

$$I(x,y,t+\Delta t) = I(x,y,t) + k\sqrt{1+I_x^2(x,y,t)+I_y^2(x,y,t)}\Delta t + o(\Delta t) \tag{4}$$

where $o(\Delta t)$ represents the error of the approximation.

2.2 Edge Detection

In [5] a fuzzy edge detection method is described which offers a way to qualify edges according to their fuzzy edge-ness (i.e., how strong edges they are). By this, the evaluation of the sum of intensity changes can be turned to a task where the edge points weighted by their fuzzy edge-ness are summed. The fuzzy interpretation of the intensity differences leads to life-like results.
Let the pixel luminance of the original image at location $[x,y]$ be denoted by $z_{0;x;y}$. Considering the group of neighboring pixels which belong to a 3x3 window centered on $z_{0;x;y}$, the output of the edge detector is yielded by the following equation:

$$\begin{aligned} z_{x,y}^{p} &= (L-1)MAX\left\{m_{LA}(\Delta v_1), m_{LA}(\Delta v_2)\right\} \\ \Delta v_1 &= \left|z_{0,x-1,y} - z_{0,x,y}\right| \\ \Delta v_2 &= \left|z_{0,x,y-1} - z_{0,x,y}\right| \end{aligned} \tag{5}$$

where $z^p_{x,y}$ denotes the pixel luminance in the edge detected image and m_{LA} stands for the used membership function. $z_{0,x-1,y}$ and $z_{0,x,y-1}$ correspond to the luminance values of the left and upper neighbors of the processed pixel at location $[x,y]$. L-1 equals to the maximum luminance value (e.g. 255). For more details about fuzzy edge detection, see [4].

2.3 Edge Separation

The most characteristic edges of the objects are extracted in the smoothed image with the help of the constructed edge map of the original picture. For each edge point of the original picture, the environment of the point is analyzed in the smoothed image. The analysis is realized by calculating the mean squared deviation of the color components in that environment.
Let $\mathbf{p}=[p_x, p_y]$ be an edge point in the original image and let $\mathbf{M}$ denote a rectangular environment of $\mathbf{p}$ with width w and height h. The mean squared deviation d is calculated, as follows:

$$d = \frac{\sum_{i=p_x-w/2}^{p_x+w/2} \sum_{j=p_y-h/2}^{p_y+h/2} (\mu_{RGB} - I_{RGB}(i,j,t_{stop}))^2}{hw} \tag{6}$$

where t_{stop} represents the duration of the surface deformation and μ_{RGB} corresponds to the average level of the color inside $\mathbf{M}$. If d exceeds a predefined threshold value, then the edge point is considered as boundary edge.

2.4. Determination of the Fuzzy Level of Details

The fuzzy information level of the image can be evaluated by simply summing the membership values (m_{LA}) of the boundary edge pixels ($\mathbf{p}_b$)

$$M_D = \sum_i m_{LA}(\mathbf{p}_{bi}). \tag{7}$$

As higher is the calculated M_D value in image region R as detailed the analyzed region is.

3. The Adaptive Fuzzy Information Measure Based Mapping Function

The FLDs can be used to scale the intensity/color transformation of the regions (e.g. in case of High Dynamic Range (HDR) images, between the visible and HDR light intensity ranges). As starting, any suitably simple, monotonous, low complexity (e.g. logarithmic) mapping function can be used. This easily evaluable function can be combined with a locally tuned nonlinear scaling (of the luminance/color values) thus, extending the mapping possibilities.

The mapping function makes possible to compress regions where unimportant or sparse information is stored thus, offering a way to keep wider parts of the displayable or viewable domain for the important (dense) regions. The importance of the regions can be estimated easily and automatically by the FIM. The output luminance/color regions can be allocated proportional to M_D. The mapping will keep the relativity of the luminance, i.e. lighter regions will remain lighter while darker regions darker. Similarly, the "character" of the scene/picture will also remain (i.e. more characteristic ranges will have greater contribution to the output luminance/color values of the pixels).

In Fig. 1 a possible mapping function combined with a simple nonlinear vertical axis of the displayable luminance values is shown. The nonlinearity of the vertical axis is influenced by a set of linear functions. By changing the linear functions the nonlinear characteristics of the vertical axis can also be modified.

$$\begin{array}{llll} \text{if} \quad 0 \le \log(L_w) \le a & \text{then} & L_d = \log(L_w)/\cos \propto_1 & \\ \text{if} \quad a < \log(L_w) \le b & \text{then} & L_d = \log(L_w)/\cos \propto_2 & \\ \text{if} \quad b < \log(L_w) \le c & \text{then} & L_d = \log(L_w)/\cos \propto_3 & \text{where} \end{array} \tag{8}$$

$$a = SW1; b = (SW1 + SW2); c = (SW1 + SW2 + SW3) \text{ and}$$
$$SW1/\cos \propto_1 + SW2/\cos \propto_2 + SW3/\cos \propto_3 = L_{dmax}$$

Here L_w denotes a wide range value and L_d stands for the corresponding displayable value with upper limit L_{dmax} (i.e., after determining the adaptively modified widths of the sections, the total length of the transformed range has to be scaled to the total width of the displayable range). SWi represents the width of region i in the logarithmic scale, and α_i is the angle between the side of the section i of the axis and the original vertical axis. The α_i angles are tuned according to M_{Di}.

4. Fuzzy Information Measure Based Image Quality Improvement

Digital signal processing techniques can often improve the visual quality of photos and sceneries. The goal of noise filtering, image information enhancement methods, image sharpeners, etc. is to enhance and preserve visual information while suppressing noise [6]. The aim of HDR imaging techniques (anchor based algorithms [7], tone mapping function based algorithms [8], multiple

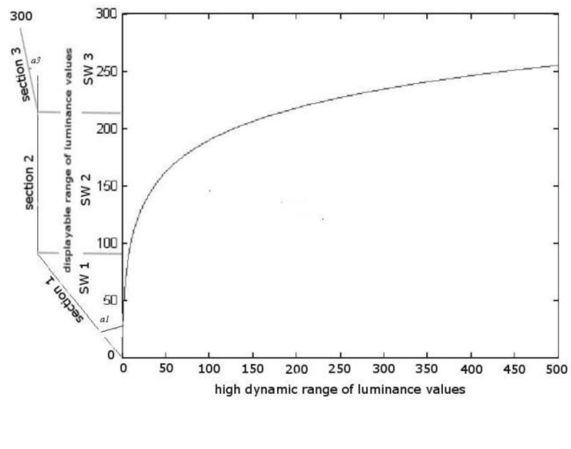

Fig. 1. Example for the proposed adaptive FIM based mapping function: logarithmic mapping combined with nonlinear (or piecewise linear) vertical axis

exposure time synthesization techniques [9], image sensors [10], etc.) is to transform values which cover an intensity/color range that is too wide to be displayed or to be captured by the human eye to a visible domain while trying to preserve the quality of the scenery and as much details as possible [11]. This type of quality improvement can be achieved at “normal” images, as well, if the close by (in space and/or in color) details are shifted by an appropriate transformation. The proposed FIM based mapping function can be applied to scale the transformation. Some examples:

- anchor based algorithms: The FLD value (M_D) has to be determined for each framework. The local anchors can be relocated according to the value of the corresponding M_D in such a way that the distances between the anchors reflect the magnitude of the M_D –s. They can be considered in the articulation factors as well.
- tone mapping function based algorithms: the FIM based mapping function can directly be used as tone mapping function.
- multiple exposure time image synthesization: FIM can be used to help choosing the most detailed exposure for the analyzed local image region. After creating the temporary image (which contains the most detailed local image regions), before further processing (smoothing, etc.) the regions can be re-scaled according to their M_D values.
- “normal” images: the image can be divided into local regions and the sizes of the domains can be geared to each other. The locally determined M_D-s can be used as measure of the re-scaling.

5. Fuzzy Information Measure Based Improvement of the Visual Sensing

Today, improvement of the quality of color perception has become an important research field followed with increased attention all around the world. At one hand, it may offer at least partial solution for color vision problems of color deficient people, while on the other hand may improve the color capturing capability of people having good color vision. At first glance the two approaches seem different. Although, if we analyze them more deeply, it turns out that both aims to match the offered/sensed color spectra with the (individual or general) human color perception process in order to optimize the color differentiation capability and perceptible color gamut. In general, it can be achieved by ensuring a maximum distance uniform distribution of perceptible colors in the color space transmitted to the brain.

The color of an object is determined by the spectral power distribution (SPD) of the light reflected from its surface depending on the spectral reflection of the object and the SPD of the illumination

$$\Phi_1(\lambda) = \Phi_0(\lambda))\rho(\lambda) \tag{9}$$

where $\Phi_1(\lambda)$ denotes the SPD of the light which specifies the color of the surface, $\Phi_0(\lambda)$ stands for the SPD of the illumination, and $\rho(\lambda)$ is the spectral reflection of the color surface.

If a color filter is placed in the path of the light, the sensed SPD of the light reflected from the color surfaces changes, i.e. the surface looks different color. This relationship can be described as

$$\Phi_2(\lambda) = \Phi_0(\lambda)\tau(\lambda)\rho(\lambda)) \tag{10}$$

where $\tau(\lambda)$ stands for the spectral transmission of the filter.

The same color difference increasing effect can be achieved by modifying the SPD of the light illuminating the surface of objects. This latter can be achieved by the modification of the spectral characteristics of the (artificial) lighting [12]. The lighting has a non-linear filtering effect (modifying the spectral characteristics of the light reflected by different colored surfaces) and can efficiently be controlled based the M_D values of the environment.

In Fig. 2 an example is shown which illustrates the effect of using such a modifying filter. In the left hand side of the figure, the normal SPD of a CIE A light source can be followed. In the middle, the characteristics of a modifying filter is presented. This filter shifts the SPD of the shorter wave length lights to left and the longer wavelength lights to right while in the middle range the spectral

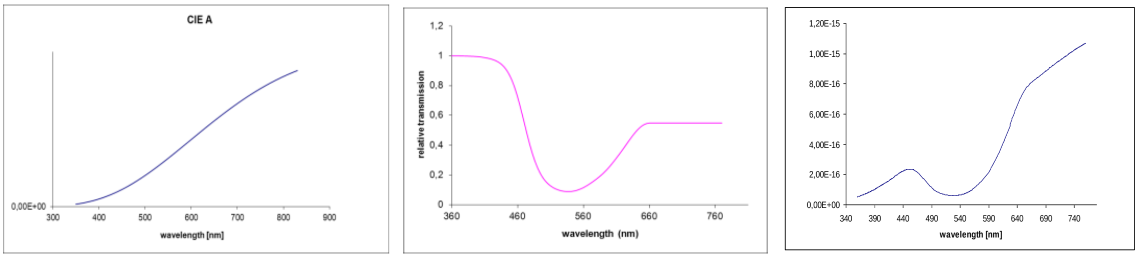

Fig. 2. SPD of the CIE A light source (left); Spectral transmission of the color difference increasing (middle); The resulting filtering effect on the light source (right)

transmission of the filter is nearly constant thus, the SPD of the lights in this range is only slightly changed. The resulting transmission characteristics can be followed in the right hand side part of the figure [12]. It well illustrates the case when the shorter and the longer wavelength ranges have to be increased for better color discrimination. By applying other filter characteristics, different shifting effects can be achieved.

If we evaluate the local M_D-s in the color space of an environment, the regions to be modified can be determined, from which the necessary filter characteristics yields. The filtering effect can be achieved by tuning the spectral characteristics of the (artificial) lighting.

6. Conclusion

The limited color and light intensity capturing abilities of the human eye may cause serious distortions and problems in the viewing and further processing of digital images and real life's scenes. Important information can be hided in the dense, highly, or lowly illuminated parts. This paper proposes a new fuzzy information measure which can advantageously be used in image reproduction and image feature extraction. Based on the fuzzy measure an adaptive, nonlinear, information amount based transformation technique is also proposed by which the hardly or non-viewable features and content of the images can adaptively be developed.

Acknowledgment

This work was supported by the Hungarian National Scientific Fund (OTKA 105846).

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