A Novel Tone Mapping Based on Double-Anchoring Theory for Displaying HDR Images

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SUMMARY In this paper, we present a Double-Anchoring Based Tone Mapping (DABTM) algorithm for displaying high dynamic range (HDR) images. First, two anchoring values are obtained using the double-anchoring theory. Second, we use the two values to formulate the compressing operator, which can achieve the aim of tone mapping directly. A new method based on accelerated K-means for the decomposition of HDR images into groups (frameworks) is proposed. Most importantly, a group of piecewise-overlap linear functions is put forward to define the belongingness of pixels to their locating frameworks. Experiments show that our algorithm is capable of achieving dynamic range compression, while preserving fine details and avoiding common artifacts such as gradient reversals, halos, or loss of local contrast.

key words: double-anchoring theory, lightness perception, tone mapping, segmentation, high dynamic range

1. Introduction

High Dynamic Range (HDR) images can contain real world luminance level and be represented by more than 8-bit per channel. They can capture a much higher level of details and are close to the perception of human visual system. Moreover, HDR images store linear values, which means that the value of a pixel in a HDR image is proportional to the value of light measured by a camera. In this sense, the HDR images fully store information of scenes. However, the HDR images have a problem with their application in that they cannot be displayed correctly on common display devices such as printers or monitors. That is why tone mapping algorithms are designed, which scale the large range of luminance information that exists in the real world so that a HDR image can be displayed on a device that has a much lower dynamic range. Nevertheless, most current tone mapping algorithms can not achieve compression well when the dynamic range is very high. In this situation, the problems such as gradient reversals, halos, or loss of local contrast are still not be solved.

In paper [1], luminance is defined as the amount of light projected to the eyes, it is determined by a number of factors: the illumination that strikes visible surfaces, the proportion of light reflected from the surface, and the amount of light absorbed, reflected, or deflected by the prevailing atmospheric conditions. Among these factors, the proportion of light reflected from the surface is known as lightness, which is associated with the intrinsic property of surfaces. That is to say, lightness is a perceptual quantity measured by the human visual system (HVS). If a visual system only made a single measurement of luminance, there would be no way to distinguish a white surface in dark light from a black surface in bright light. Yet, HVS can usually do so, and this skill is known as lightness constancy. Lightness constancy is an important characteristic of the HVS, which leads to a similar appearance of the perceived objects independently of the lighting and viewing conditions [2].

As we know, a gray patch appears brighter when viewed against a dark background and darker when viewed against a bright background. This effect is known as simultaneous lightness contrast. In [3], in order to relate the luminance to the lightness, a criterion between the luminance value and the perceived gray shades is defined. The criterion is called anchor. Once such an anchor is obtained, the lightness value for each luminance value can be estimated by the ratio between the luminance value and the anchor. In practice, two different approaches related to anchoring’s definition are known: the highest luminance rule and the average luminance rule. Highest Luminance Rule: The value of white is assigned to the highest luminance in a display and serves as the criterion for darker surfaces [4]. Average Luminance Rule: The average luminance in a visual field is perceived as middle gray. It is served as a criterion value. The lightness values of both darker and lighter surfaces can be obtained by the ratio values between their luminance value and the criterion value.

In this paper, in order to solve the artifact problems when the dynamic range for HDR images are very high, a Double-anchoring Based Tone Mapping (DABTM) method is proposed. We use the two anchor values obtained by the double-anchoring theory to formulate a novel compressing operator, which can achieve the aim of tone mapping directly. In the double-anchoring model, the first anchor is the highest luminance and the second anchor is the surrounding luminance, and a framework is defined by regions in terms of common illumination. We adopt a new K-means algorithm to decompose HDR images into frameworks, which can be less time-consuming. Most importantly, a group of piecewise-overlap linear functions is proposed to define the belongingness of pixels to their locating frameworks. In the experimental section, a tool called HDR-VDP is used to evaluate the relative effectiveness of DABTM.

The paper is organized in the following way. Section 2 provides an overview of existing tone mapping operators.
We illustrate the DABTM method in detail in Sect. 3. In Sect. 4, the effectiveness of our algorithm is verified by experiments on images with different contents. We conclude the paper in Sect. 5.

2. Previous Works

The tone mapping was first defined by photographers. Their goal was to obtain realistic reproduction of captured scenes. Tone mapping for HDR images has been extensively studied in computer graphics for over a decade. In this section we provide a brief review of previous works.

In the retinex [5] model, it was assumed that for remote image regions, ratio of luminance at edges was determined through the edge integration of luminance ratios along an arbitrary path connecting those regions. Lightness could be well modeled by the retinex algorithm when the illumination changed slowly, while when the illumination changed shapely, the pixels of sharp borders could not be properly processed. Gilchrist et al. proposed that the HVS performed an edge classification to distinguish illumination and reflectance edges [6]. This led to the concept of the decomposition of retinal images into so-called intrinsic images with reflection layer, illumination layer and so on. Lots of lightness perception theories based on intrinsic images could process lightness constancy very successfully. However, they had problems with simulating the failures of lightness constancy. To overcome this problem, Gilchrist et al. [4] developed an anchoring theory of lightness perception. The anchoring theory was able to model the lightness constancy failure and assign the absolute lightness to per pixel.

Tumblin et al. [7] proposed a model of brightness perception based on the power-law relationship developed by Stevens et al. [8] between the brightness and the corresponding luminance. The main goal was to preserve a constant relationship between the brightness of a scene perceived on a display and its real counterpart for any lighting condition. The algorithms [9], [10] based on threshold models of the contrast perception for the scene luminance could achieve to compress in HDR images. Further attempts in lightness reproduction led to direct application of the retinex theory [5] to tone mapping. Jobson et al. [11] proposed a multi-scale retinex algorithm for luminance compression, which unfortunately led to halo artifacts for the HDR images along high contrast edges. The method of Reinhard in [12] applied a so-called zone system to HDR images compression. Inspired by the lightness perception model developed by Horn [13], Fattal et al. [14] proposed a successful gradient domain tone mapping operator. A concept of intrinsic images based on separating the illumination and reflectance layers inspired many algorithms. The high contrast of the illumination layer was usually reduced by scaling, while the details layer was preserved. The LCIS operator [15] separated the image into large scale features and fine details. A better separation had been achieved using the bilateral filter [16]. Krawczyk et al. [18] proposed a method based on anchoring theory developed by Gilchrist et al. [4]. A perceptual framework for contrast processing of HDR image was derived in [19]. Methods based on uniform brightness functions suffered from the loss of details due to compression. The intrinsic image models could not achieve compression well when the dynamic range of HDR images are quite high. The problems such as halos and loss of local contrast remain unsolved.

3. A Double-Anchoring Based Tone Mapping Method

In this section, we describe how to make use of two anchor values to the HDR images rendering. The algorithm takes a HDR image defined by floating point RGB values as input, and produces a displayable LDR image as a result. The compression processing is solely applied in the luminance channel.

We first decompose the input image into frameworks. Next, the strengths of each pixel to its locating frameworks are calculated. Third, we estimate the anchors in each framework, i.e. the highest luminance value and the surrounding luminance value perceived as white. Finally, the final compressed value for each pixel is calculated by the two anchoring values based compression operator.

3.1 Decompose the Image into Frameworks

The double-anchoring rule described in the previous section can not be applied directly to complex images. The paper [4] proposed the concept based on the decomposition of the image into so-called frameworks, in which the anchoring rule can be applied directly. The frameworks are defined by regions of having similar illumination. For instance, all objects under the shadow would be composed of a framework.

In paper [18], it started with the standard K-means clustering algorithm to find the centroids. It executed iterations until the K-means algorithm converged and followed by the removing and combining centroids operations. For all experimental HDR images in this paper, after merging, only two or three centroids were remained, that is to say, the image was only decomposed into two or three frameworks. The iteratively removing and combining processes increase the amount of time needed. These arguments serve as a motivation to adopt an improved method [20]. The algorithm avoided unnecessary distance calculations by applying the triangle inequality in two different ways and by keeping track of lower and upper bounds for distances between points and centers in order to enhance efficiency. In DABTM, we initialize the K-means algorithm with user parameter \( k = 3 \), which means that we decompose the image into three frameworks directly. Notice that we use \( k = 3 \) to decompose the HDR image into three frameworks directly referring to the Krawczyk’s experimental conclusion. However, \( k = 4 \) or \( k = 5 \) might be more appropriate, how to define its value adaptively according to the characteristic of HDR images is my future work about DABTM. As a result, three centroids can be obtained in our paper.

The K-mean clustering algorithm operates on the his-
framework and Light framework. In DABTM, we process these pixels in single framework using our proposed method. In Fig. 1, the red, cyan and green regions denote the Dark framework, Visible framework and Light framework defined above respectively.

When a pixel between two frameworks has a smooth gradient in the image and is assigned to only one framework, in such situation it is impossible to process correctly. In DABTM, the pixels between the first centroid and third centroid belong to two frameworks and have different lightness value when anchored within each framework. The belongingness is decided by the piecewise-overlap linear functions described in the following section. For the pixels in the dark areas and in the highlight areas, that is to say, pixels’ value are smaller than the first centroid or the pixels’ value are larger than the third centroid, pixels’ details are more focused on. In DABTM, we process these pixels in single framework.

$$I_L(x, y) = 0.213R(x, y) + 0.715G(x, y) + 0.072B(x, y)$$ (1)
$$I(x, y) = \log_{10}(\max(I_L(x, y), 0.0001))$$ (2)

where $R(x, y), G(x, y)$ and $B(x, y)$ are the three color channel values, $I_L(x, y)$ represents the original luminance value. Since the logarithm of zero is negatively infinite and the lowest threshold of human vision is $10^{-4}$ cd/m$^2$, the minimum of $I_L(x, y)$ is set to $10^{-4}$.

Given the three centroid values, we first sort the three centroid values in ascending order shown as $[c_1, c_2, c_3]$. The two medium values $[(c_1 + c_2)/2, (c_2 + c_3)/2]$ can be obtained, which are served as boundaries for decomposing the image into frameworks:

- Dark framework $= \{I(x, y)|I(x, y) < (c_1 + c_2)/2\}$
- Visible framework $= \{I(x, y)|(c_1 + c_2)/2 \leq I(x, y) \leq (c_2 + c_3)/2\}$
- Light framework $= \{I(x, y)|I(x, y) > (c_2 + c_3)/2\}$

In Fig. 1, we demonstrate the frameworks maps of the images used in our experiment. We can see the regions of common illumination can be decomposed into a framework using our proposed method. In Fig. 1, the red, cyan and green regions denote the Dark framework, Visible framework and Light framework defined above respectively.

To reproduce as many details of the image as possible, we do not simply consider the belongingness values during the determination of the output compressed value of one pixel. The relative entropy value of one framework is also used to influence the strength of its locating framework. The formula of entropy value is defined as follows:

$$B_1(x, y) = \frac{I(x, y) - \min}{\max - \min}I(x, y) < c_1$$
$$B_2(x, y) = \frac{I(x, y) - c_1}{c_2 - c_1}c_1 \leq I(x, y) < c_2$$
$$B_3(x, y) = \frac{I(x, y) - c_2}{c_3 - c_2}c_2 \leq I(x, y) \leq c_3$$
$$B_4(x, y) = \frac{\max - I(x, y)}{\max - c_3}I(x, y) > c_3$$

where $B_i(x, y)$ denotes the belongingness to framework $i$ for pixel $I(x, y)$, which represents the luminance value defined in Eq. (1).

The shapes of Eq. (4) are shown as in Fig. 2. We can see that output related to the red line denotes the belongingness to the Dark framework, the black line denotes the belongingness to the Visible framework, and the blue line denotes the belongingness to the Light framework. Taking one pixel $I(x, y)$ as example, the output related to the yellow line represents belongingness to the Visible framework and green line represents belongingness related to the Light framework respectively.

To reproduce as many details of the image as possible, we do not simply consider the belongingness values during the determination of the output compressed value of one pixel. The relative entropy value of one framework is also used to influence the strength of its locating framework. The formula of entropy value is defined as follows:

$$I(x, y) = \log_{10}(\max(I_L(x, y), 0.0001))$$

Fig. 1  The framework map of the tested images. (A) Original images. (B) Framework maps.

Fig. 2  The piecewise-overlap linear functions of belongingness.
where \( E(F_i) \) represents the entropy value for the framework \( i \), \( Bin \) denotes bin’s index value of the whole luminance histogram in log10 space, \( p(Bin) \) represents the probability value, which is defined by the number of pixels related to bin \( Bin \) divided by pixels’ number of its locating framework. \( mBIF_i \) denotes the max bin’s index value for the framework \( i \).

The final entropy value of one framework is defined as:

\[
E_n(F_i) = \frac{E(F_i)}{\sum_{i=1}^N E(F_i)}
\]

(6)

where \( E_n(F_i) \) represents the entropy value of the framework \( i \), \( N \) is the number of frameworks. In DABTM, \( N = 3 \).

For one pixel, after the entropy value related to locating framework has been calculated, we have to multiply the value by the corresponding belongingness value defined as in Eq. (4) to decide the final strength for one framework. The formula is defined as follows:

\[
Pr_i(x, y) = B_i(x, y) \times E_n(F_i)
\]

(7)

where \( i \) denotes the locating framework for pixel \([x, y]\).

### 3.3 Anchor Estimation and Compressing Operator

After the decomposition into frameworks has been done, we estimate the anchor values within each framework independently. Since we employ the double anchoring theory, we need to find the highest luminance value and surrounding luminance that would be perceived as white. According to the surrounding luminance represented in paper [3], there was no specific definition for complex image. In DABTM, we propose a new method to define the surrounding luminance. Next, we will describe the details for the estimation of the two anchors.

Although we apply the highest luminance rule, we can not directly use the highest luminance in the framework as an anchor. When the highest luminance does not cover the largest area, the highest luminance starts to be perceived as self-luminous. In order to solve this problem, we can decrease the effect with removing a certain amount, e.g. 3%, of the highest luminance pixels in that framework and then take the highest luminance value of the rest pixels as the highest luminance anchor.

There is a relationship between the pixel’s luminance value and its neighboring domain luminance value. In DABTM, we use a spatial filtering to filter the whole image with a large Gaussian kernel, and get the weighted average luminance value to serve as surrounding luminance \( S \) for each pixel in the image. The formula is defined as follows:

\[
S(x, y) = G_{\sigma_{s}}(x, y) \otimes I(x, y)
\]

(8)

where \( G_{\sigma_{s}} \) is a Gaussian function with kernel \( \sigma_{s} \). In the experiment, we set \( \sigma_{s} = 20 \).

As the final step, we compute the compressed value for each pixel by merging its locating frameworks. The proposed compression operator is defined according to the two anchor values and the strength of its locating frameworks. The formula is defined as follows:

\[
L(x, y) = \alpha \sum_{i} ( (I(x, y) - H_{i} - \beta S(x, y)) (1 - \alpha)(I(x, y) - H_{i})
\]

(9)

where \( L(x, y) \) denotes the final compressed luminance value, \( I(x, y) \) is the original luminance value, \( H_{i} \) is the highest luminance value of framework \( i \), \( S(x, y) \) is the surrounding luminance anchor for pixel \([x, y]\), \( H_{s} \) is the highest luminance value in the whole image, all the values are in the log10 space. \( Pr_i(x, y) \) is the strength of framework \( i \) defined as in Eq. (7).

It seems that the proposed operator Eq. (9) is similar to Eq. (5) in [18] about achieving dynamic range compression for HDR images. Notice that Eq. (5) in [18] is only used to obtain the perceived stimuli, yet it does not achieve dynamic range compression well for HDR images. So it must be included another reduction factor \( D_{i} \) defined in Eq. (6) to achieve compression for HDR images. In our paper, we only use the two anchoring values to formulate the compressing operator, which can achieve the aim of tone mapping directly. Next, we describe the physical meaning of Eq. (9) in detail.

As we known, given a range \([a, b]\), where \( a \) indicates the minimum value, \( b \) indicates the maximum value, we can reduce the range with another range \([m, n]\) on the condition \( b - a \geq n - m \) that can make the original sort order unchange. Mathematically, the rule can be described by \([a+n+b-m]\). The distance of obtained new range is \( b + m - (a + n) = (b-a)+(m-n) \). The negative value of \((m-n)\) and \(b-a \geq n-m\) result in \(|b + m - (a + n)| < |b - a| \). That is to say, the range of original \([a, b]\) is compressed. We also view that the larger is the range scope \([m, n]\), the smaller is the new compressed range for \([a, b]\).

As to Eq. (9), we explain the physical meaning from two points. Firstly, we use the sign ‘+’ to divide the Eq. (9) into two parts. The former part is related to the range \([m, n]\) and the latter one is related to the range \([a, b]\) mentioned above. Due to the float-point store characteristic for HDR images and the normalizing [0 1] process, the values of luminance are negative in log10 space. Our objective is to move the histogram to the range [0 2] that is the range for common display device (0-255 in log10 space). We know that the dynamic range for a HDR image is uncertain, for example, the minimum value may be \(-6\) and the maximum value may be \(-2\), or the minimum value may be \(-4\) and the maximum value may be \(-1\). The subtracting operation using \(H_{s}\) in the latter part can achieve the global histogram
move to “0” point. However, the overall dynamic range is unchanged. Secondly, we make use of the former part in Eq. (9) to achieve dynamic range compression. Analysis is described as follows: we use \( I_0(x) \) and \( I_1(x) \) to represent the luminance values for two treated pixels in a HDR image, and suppose \( I_2(x) > I_1(x) \). Our main aim is to obtain relative small value for \( I_2(x) \) and relative large value for \( I_1(x) \). The distance of the two treated pixels is \( I_2(x) - I_1(x) \) before processing. After processing using the former part in Eq. (9), the distance becomes \( I_2(x) - H - \beta S(x) - (I_1(x) - H - \beta S_1(x)) \). Since \( S \) denotes the luminance value of neighboring domain around one treated pixel, here we make the assumption that \( S_2(x) = I_2(x) \) and \( S_1(x) = I_1(x) \), then the distance between the two targets is defined as follows:

\[
\begin{align*}
I_2(x) - H - \beta I_2(x) - (I_1(x) - H - \beta I_1(x)) \\
= I_2(x) - I_1(x) + \beta(I_1(x) - I_2(x)) \\
= (\beta - 1)(I_1(x) - I_2(x))
\end{align*}
\]

We can conclude that: (1) if \( 0 \leq \beta < 1 \), the result is positive, the obtained value for \( I_2(x) \) is still larger than that of \( I_1(x) \). (2) if \( \beta = 1 \), the results for two treated pixels are same. (3) if \( \beta > 1 \), the result is negative, that is to say, the new value for \( I_2(x) \) is smaller than that of \( I_1(x) \), which is the goal in our paper. However, the new distance for \( I_1(x) \) and \( I_2(x) \) may become large due to parameter \( \beta \). To make the original sort order to be unchanged (new compressed value for \( I_2(x) \) is still larger than that of \( I_1(x) \)), we use the other parameter \( \alpha \) to ensure \((\beta - 1)(I_1(x) - I_2(x)) = \alpha \leq I_1(x) - I_2(x) \), that is, \((\beta - 1) \leq \frac{1}{\alpha} \). In our paper, we limit \( \beta \in [3, 7] \) and \( \alpha \in [0.5] \) for HDR images, which can make use of the full range of common display device as possible and achieve pleasant results.

4. Experiment Results

A good tone mapping algorithm should be image independent and capable of providing "nice-looking" results regardless of the input image content [21]. In our experiment, to verify the proposed tone mapping algorithm DABTM, we adopt images that include a variety of image contents. All the experiments are implemented in Matlab 7.0 and run on a Pentium (R) 4 CPU 3.0-GHz machine with 1-G RAM.

As to the parameter \( \beta \) defined in Eq. (10), we present a technique to determine its value according to input HDR images in our paper. We make use of \( D \) to denote the dynamic range of a HDR image, that is, the ratio between maximum luminance value and minimum luminance value in log10 domain of input HDR image. Based on extensive experiments, we find that when \( \beta \in [D - 1D + 1] \), DABTM can generate pleasant results for most HDR images with various dynamic ranges. At present, we can just limit the range that \( \beta \) belongs to, and how to get the optimal value for one image will be done in our future work about DABTM. In our paper, for all the testing HDR images, we provide the histograms of original images in log10 domain to show the dynamic range values, which can demonstrate visually that the proposed algorithm DABTM is applicable to images with various high dynamic ranges. The value of dynamic range \( D \) of each input HDR image is served as the default value of parameter \( \beta \) in our experiments.

We adopt a novel tool called HDR-VDP [22] to validate the performance of tone mapping algorithms directly. More details can be seen as follows. In our experiments, we use two HDR images provided by Laurence Meylan to verify the performance of DABTM. Nine algorithms are considered: Drago [23], Fattal [14], Pattanaik [24], Reinhard02 [12], Reinhard05 [17], Meylan06 [25], Meylan07 [26], Yuanzhen Li [27], single anchor based algorithm and the proposed algorithm DABTM. These algorithms can give visually pleasing results in making detail visible in both the bright and dark regions. The visual comparison among these algorithm can be seen from the result images in Fig. 3-6. Every group consists of a mapped result and a HDR-VDP output map. From the mapped images, we can see that the proposed algorithm DABTM can provide a close visual performance to other algorithms in displaying high dynamic range images. However, there are also some differences in contrast, sharpness and detail preserving. In our paper, these differences can be observed using the HDR-VDP map of corresponding mapped image. The HDR-VDP is a perceptual metric, which is presented by Mantiuk et al.. The HDR-VDP tool is available, which can be found in ‘http://www.mpipiinf.mpg.de/resources/hdr/vdp/index.html’. In the process of HDR-VDP, both the mapped LDR images and the original HDR images are converted to the JND-scale space firstly, and the output of the HDR-VDP is a map of probability for detecting visible differences, that is, each pixel position has a corresponding probability. When an algorithm obtains a HDR-VDP map with more pixels with a lower probability, it can be considered to produce a better visual quality. The probability maps of the HDR-VDP are expressed as different colors, which are used to represent different ranges of probability. The grey color is used to represent the probabilities from 0 to 0.25, green for the probabilities from 0.25 to 0.5, yellow for the probabilities from 0.50 to 0.75, red for the probabilities from 0.75 to 0.95, and pink for the probabilities from 0.95 to 1.0. In a HDR-VDP maps, one region in red means there is a significant visual difference between the original HDR image and the mapped image at that region, while a grey region implies a small visual difference from the original scene.

The HDR-VDP map of each result image is displayed in Fig. 3-6. We can see that grey-regions obtained by DABTM are larger than those of other tone mapping algorithm. In order to show the result quantitatively, the probability values of detection \( P > 75\% \) and \( P > 95\% \) related to test images in Fig. 3-6 are given in Table 1. From Table 1, it can be seen that our algorithm DABTM produces the best result compared to other algorithms. For example, the probability value is 12.04% for \( P > 75\% \) for the image in Fig. 3, which is smaller than other results of nine tone mapping algorithms. The probability value is 6.81% for \( P > 95\% \), which is the smallest one among nine algorithms. Same conclusion can be obtained for the images in Fig. 4-6. Based on
Fig. 3  Comparison results compared to other typical tone mapping methods. Every group consists of mapped result and HDR-VDP result. (A) Drago [23], (B) Fattal [14], (C) Pattanaik [24], (D) Reinhard02 [12], (E) Reinhard05 [17], (F) Meylan06 [25], (G) Meylan07 [26], (H) Yuanzhen Li [27], (I) single anchor based algorithm. (J) DABTM. The image courtesy of Laurence Meylan.
Fig. 4  Comparison results compared to other typical tone mapping methods. Every group consists of mapped result and HDR-VDP result. (A) Drago [23]. (B) Fattal [14]. (C) Pattanaik [24]. (D) Reinhard02 [12]. (E) Reinhard05 [17]. (F) Meylan06 [25]. (G) Meylan07 [26]. (H) Yuanzhen Li [27]. (I) single anchor based algorithm. (J) DABTM. The image courtesy of Laurence Meylan.
Fig. 5 Comparison results compared to other typical tone mapping methods. Every group consists of mapped result and HDR-VDP result. (A) Drago [23]. (B) Fattal [14]. (C) Pattanaik [24]. (D) Reinhard02 [12]. (E) Reinhard05 [17]. (F) Meylan06 [25]. (G) Meylan07 [26]. (H) Yuanzhen Li [27]. (I) single anchor based algorithm. (J) DABTM. The image courtesy of Durand and Dorsey.
Fig. 6  Comparison results compared to other typical tone mapping methods. Every group consists of mapped result and HDR-VDP result. (A) Drago [23]. (B) Fattal [14]. (C) Pattanaik [24]. (D) Reinhard02 [12]. (E) Reinhard05 [17]. (F) Meylan06 [25]. (G) Meylan07 [26]. (H) Yuanzhen Li [27]. (I) single anchor based algorithm. (J) DABTM. The image courtesy of Dani Lischinski.
Table 1 The probabilities of detection when $P > 75\%$ and $P > 95\%$.

| Image | method | $P > 75\%$ | $P > 95\%$ |
|-------|--------|-------------|-------------|
| A     |        | 32.58\%    | 24.37\%    |
| B     |        | 48.30\%    | 35.93\%    |
| C     |        | 18.81\%    | 12.93\%    |
| D     |        | 41.31\%    | 33.07\%    |
| E     |        | 20.05\%    | 14.51\%    |
| F     |        | 27.38\%    | 21.62\%    |
| G     |        | 26.39\%    | 18.57\%    |
| H     |        | 35.79\%    | 21.93\%    |
| I     |        | 17.21\%    | 9.40\%     |
| J     |        | 12.04\%    | 6.81\%     |

Fig. 3

Fig. 4

Fig. 5

Fig. 6

the above analysis, we can see that the proposed algorithm DABTM is effective and is superior to other tone mapping algorithms compared in our paper in terms of HDR-VDP output map.

At last, we explain in particular why the double-anchoring based DABTM gives the change to the result image compared to single-anchoring based method. The visual comparison can also be seen in Fig. 3-6 in images (I) and images (J). We can see that more details of images (J) obtained by DABTM can be viewed. As to the definition of Eq. (10), we use $I^D_{\text{new}}(x) - I^S_{\text{new}}(x) = (\beta - 1)(I_1(x) - I_2(x))$ to denote new range of $I_1(x)$ and $I_2(x)$. $(I_1(x)$ and $I_2(x)$ represent the luminance values for two pixels, and suppose $I_2(x) > I_1(x)$). Our main aim is to obtain relative small value for $I_2(x)$ and relative large value for $I_1(x)$, which can achieve dynamic range compression, that is, $I^D_{\text{new}}(x) - I^S_{\text{new}}(x) < 0$. When $\beta = 0$ (single anchoring based), $I^D_{\text{new}}(x) - I^S_{\text{new}}(x) = I_2(x) - I_1(x) > 0$, the dynamic range can not be compressed. It only achieve the global histogram move to “0” point. When $\beta > 1$ (double anchoring based), then, $I^D_{\text{new}}(x) - I^S_{\text{new}}(x) < 0$, that is, the new value for $I_2(x)$ is smaller that that of $I_1(x)$, the dynamic range not only moves to “0” point, but also is compressed. That is why the images obtained by our proposed algorithm DABTM can preserve more details than the images obtained using single anchoring based algorithm.

5. Conclusion

In this paper, we propose a novel compression operator for tone mapping of HDR images, which is based on two-anchoring values obtained by the Double-anchoring theory [3]. We adopt an accelerated K-means algorithm based on triangle inequality to decompose HDR images into frameworks, which can reduce the amount of time needed. A group of piecewise-overlap linear functions is proposed to define the belongingness of one pixel to its locating frameworks. By using the algorithm, we can reconstruct LDR images that have less shift of local contrast and preserve more details perceived by HVS.

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