ABSTRACT
This paper presents a novel method for fusing two or more differently exposed Low Dynamic Range - LDR images of a High Dynamic Range - HDR scene. Illumination estimation is applied to coarse and fine scales leading to the contrast decomposition process at both scales and assessing to the definition of the “well-exposed” pixels in the original exposure sequence. Membership functions are then employed to ensure that well-exposed pixels from each contrast decomposed image will be selected, in order to maximize the visual information of the HDR scene. Finally, blending functions are used to create two fused images for each scale. These images contain visual information in different scales. Then, they are blended together to form the final fused image. Comparative results demonstrate that the proposed algorithm, successfully preserves the visual information of the HDR scene.

KEY WORDS
HDR Imaging, Exposure Fusion, Illumination Estimation

1 Introduction
In real-world scenes the ratio between the brightest and the dimmest point can be many orders of magnitude greater than the ratio of the brightest and dimmest pixel, that a typical camera can capture, due to the limited capabilities of the image sensor. Therefore, all the details of the scene cannot be captured in a single image and inevitably, underexposed and overexposed regions appear, (Fig. 1). A common approach to acquire such High Dynamic Range (HDR) scenes using conventional technology is to capture multiple differently exposed images and combine them into a single high-dynamic-range result. Although recent advances in display technology have suggested that HDR displays are on the horizon, for some applications such as hard copy printing, the need for dynamic range reduction is always required.

Details in high dynamic range scenes can be captured using two techniques; the HDR imaging and the Exposure fusion. HDR imaging methods use a sequence of differently exposed images to create an HDR image with a larger dynamic range of luminance values, than that of traditional images. Although HDR images will capture the full range of luminance values found in a scene, tone-mapping techniques are required to render the HDR data to the traditional low dynamic range hardware. On the other hand, exposure fusion techniques skip the creation of the HDR image and blend directly the differently exposed images into a LDR image.

In recent years, a number of tone mapping methods, which aim at reducing the brightness range of the HDR image while maintaining the contrast, were introduced. These methods can be classified into the spatially uniform (also known as global) and the spatially varying (also known as local). Spatially uniform operators may depend upon the contents of the image as a whole, as long as the same transformation is applied to every pixel. These tone-mapping methods are suitable for scenes, whose dynamic range corresponds approximately to that of the display device, or it is lower. When the dynamic range of an HDR scene exceeds by far that of the display, global tone mapping methods compress the tonal range too much. This results to a perceived loss of contrast and loss of detail visibility. On the other hand, spatially varying methods rely on the fact that humans are capable of viewing high contrast scenes due to the local control sensitivity in the retina. Thus, different functions are applied for different spatial pixel positions. In this case, one input value can result in more than one output value, depending on the pixel position and on the surrounding pixel values. In general, global tone mapping algorithms are fast and local tone mapping methods are computationally more expensive.

The Multi-exposure fusion methods eliminated the in-
termediate step of the tone mapping techniques, which was the creation of the HDR image, and produced an LDR image directly from the fusion of the multi-exposure LDR images. Mertens et al. [1] proposed a pixel level technique for exposure fusion, which generated the resultant image with the help of the saturation, contrast and well-exposedness measures. On the other hand, Goshtasby proposed a block based algorithm for exposure fusion, that increased the final image entropy [2]. The images of the exposure sequence, were divided into blocks and the ones with the highest entropy values were selected. The selected blocks of varying exposures were blended to create the final image. The method of Goshtasby could not handle object boundary and hence produced artifacts [3]. Drago [4] suggested a global tone mapping method, which performs adaptive logarithmic mapping. Reinhard [5] adapted a computational model of photoreceptor behavior to create a global tone reproduction operator. Mantiu et al. [6] proposed a tone mapping technique that can adjust image or video content for optimum contrast visibility taking into account ambient illumination and display characteristics. Fattal et al. [7] proposed a high dynamic range compression technique that manipulates the gradient field of the luminance image by attenuating the magnitudes of large gradients and then the low dynamic range image is obtained by solving a Poisson equation on the modified gradient field. Vonikakis et al. [8] performed exposure fusion, using an illumination estimation approach. Illumination estimation was applied using a single threshold resulting to a single illumination image of each exposure. In the proposed method, a low and a high threshold are used and illumination estimation is performed in both fine and coarse scales leading to two images that are used as inputs for the contrast decomposition process. Both [8] and suggested method use trapezoidal membership functions. [8] fixed thresholds for membership functions that were explicitly defined are used, while the suggested method introduces adaptive thresholds for the membership functions that are relative to the brightness of each exposure image.

In this paper, a multi-exposure image fusion method based on illumination estimation and contrast decomposition is presented. For the illumination estimation process, the spatially recursive filter proposed by Shaked et al. [9] is used. Using different sizes of the recursive filter, illumination estimation is performed in both fine and coarse scales. Illumination estimation is then used for the contrast decomposition of the Y components of each exposure in the sequence. Membership functions are then applied to the decomposed images in order to produce one fused image for each scale, which contains all contrast details of the respective scale. These membership functions ensure that well-exposed pixels will have greater weights and, thus, they will highly contribute to the fused images of the coarse and fine scales. Overexposed and underexposed pixels, on the other hand, do not contribute in order not to deteriorate the fused images. Finally, the two fused images of the different scales and the initial color information of the exposure sequence are blended to produce the final LDR image.

Experimental results demonstrate that the proposed method outperforms existing techniques preserving both original information and contrast of the scene. As a result, exposure fusion is successful producing low-dynamic range images with visual results close to the scenes, as they were captured by the different exposures.

The rest of the paper is organized as follows: the proposed algorithm is described in Section 2, experimental results and conclusions are presented in Sections 3 and 4, respectively.

## 2 Proposed Algorithm Description

The main goal of the algorithm is to extract a low-dynamic range image that preserves both contrast and visual information of a high dynamic range scene, as both were captured by the images in the exposure sequence. In order to produce naturally looking images, color information is kept untouched in the intermediate processes and a color space where luminance and color are uncorrelated is used. The selected color space is the YCbCr mainly because it is extracted from a simple linear transformation that minimizes complexity and computational time and also decorrelates the luminance component from the color components. As a result, every exposure image of the sequence is transformed from RGB to YCbCr color space. As depicted in Fig. 2, the Y component of every image is used for illumination estimation, which will be used for both the contrast decomposition process and the definition of the “well-exposedness” of pixels. Illumination estimation is performed in both coarse and fine scales. Each illumination estimation image is compared against the respective initial Y intensity values and Contrast decomposition images D are extracted for every exposure. Both contrast decomposed and illumination estimated images are used according to the membership functions M in order to define the weight W that every pixel will contribute to the final image. The details of the various stages of the method are described in the following subsections.

### 2.1 Illumination Estimation

The proposed algorithm performs illumination estimation in both coarse and fine scales leading to images used for the contrast decomposition process. These images are also used in the weight estimation function process, in order to define the degree of participation of every pixel of the exposure sequence according to its well-exposedness.

The original Retinex theory, proposed by Land et al. [10], [11] does not explicitly specify a scheme to estimate the illumination from a given image. The main computational drawback of the Retinex-like algorithms is their complexity concerning the smoothing filter, which is required to have a large kernel and in some methods reaches a complexity of more than $O(N^2)$ [9]. Shaked et al. [9] simpli-
Coarse fine

RGB YC -to- bCr

Y component

Coarse fine

Contrast Decomposition D

Membership M

Pixel Weights W

Exposures $l_1,...,l_m$ (Long exposures)

Exposures $i_1,...,i_n$ (Intermediate exposures)

Exposure $s_1,...,s_n$ (Short exposures)

Y component

Coarse fine

Contrast Decomposition D

Membership M

Pixel Weights W

Blending

$Y_{\text{out}} = f(Y_{i_1}, Y_{i_2}, Y_{i_3}, W_{i_1}, W_{i_2}, W_{i_3}, Y_{l_1}, Y_{l_2}, Y_{l_3}, W_{l_1}, W_{l_2}, W_{l_3})$

$C_{b_{\text{out}}} = f(C_{b_1}, C_{b_2}, C_{b_3}, W_{b_1}, W_{b_2}, W_{b_3}, C_{l_1}, C_{l_2}, C_{l_3}, W_{l_1}, W_{l_2}, W_{l_3})$

$C_{r_{\text{out}}} = f(C_{r_1}, C_{r_2}, C_{r_3}, W_{r_1}, W_{r_2}, W_{r_3}, C_{l_1}, C_{l_2}, C_{l_3}, W_{l_1}, W_{l_2}, W_{l_3})$

Stretching to [16,235]

Final RGB

Figure 2. Block diagram of the proposed method. $l$, $i$, $s$ are the long, intermediate, short exposures, $N_l$, $N_i$, $N_s$ are the total number of long, intermediate and short exposures, $S$ is the illumination estimation, $D$ is the contrast decomposition, $M$ is the membership function and $W$ is the pixel weight function.

Figure 3. (a) Original exposure, (b) Y component and filtering path, (c) Illumination estimation at fine scale, (d) Illumination estimation at coarse scale, (e) Magnification of original region, (f) Magnification of fine scale Illumination region.

fied the computation of illumination estimation introducing two assumptions, which include the envelope and the robustness requirements. Combining these two assumptions, the final illumination estimation is an image smoothed in
the regions where there are weak edges or uniform areas, and sharp in the strong intensity transitions. Moreover, they simplified the computation of illumination estimation introducing a recursive spatial smoothing filter. According to this, the computations are made recursively only in one dimension at a time, and in four different spatial directions of processing, in order to ensure the mixing of visual information across the whole image.

After the RGB-to-YCbCr transformation, which is applied to the initial exposures, the proposed method employs the recursive method reported in [9], to each Y component. Using the recursive filter, information flows from one pixel to the other in a single predefined path, as depicted in Fig. 3. Information though, does not flow freely, but is rather blocked in locations where the gradient of the input is below a threshold. In this way, visual information is mixed across the whole image.

In order to perform illumination estimation of the Y component in both fine and coarse scales, two different thresholds of 30 and 150 pixel intensities were selected, after extended experimentation, as demonstrated in Fig. 3. Also, the degree of well-exposedness of pixels is assessed. The goal of the algorithm is to preserve both contrast and visual information of the HDR scene while producing an LDR image. For this reason, the weight function is based on the fine and coarse contrast scales of every pixel in the exposure sequence.

2.2 Contrast Decomposition

After the illumination estimation, in order to perform the contrast decomposition [12] in the fine scale, Y intensity values are compared to the respective fine scale illumination estimation intensity values. Both values are used as inputs to a mapping function, which calculates the new intensity value of the pixel for the fine scale decomposed image. The same procedure is applied to the coarse scale. The tone mapping function aims at increasing small local intensity differences while preserving the large ones.

Finally, for every Y component of the initial exposure sequence, two images that contain contrast information of the initial scene in coarse and fine scales as demonstrated in Fig. 4 are extracted. Both contribute to the two fused images of the different scales according to their respective weights, which are extracted from the membership functions. Contrast decomposition ensures that the contrast of the scene in both scales will be preserved, to the final LDR image, which is one of the main goals of the exposure fusion techniques.

2.3 Membership Function and Pixel Weights

Membership functions are assigned to all images following the multi-scale contrast decomposition process. Pixels from all decomposed images contribute according to their illumination estimation values, in order to determine the weight that they will participate in the two coarse and fine fused images. In these fused images of every scale, all pixels of the same scale of each exposure participate according to their membership function and their weights:

\[ W_{kt}(m,n) = M_k(S_{kt}(m,n)) \]

where, \( W \) is the weight function, \( M \) the membership function, \( S \) the illumination estimation image, \( c \) the coarse scale, \( f \) the fine scale, \( t \) the long exposure, \( i \) the intermediate exposure, \( s \) the short exposure, \( N_l, N_i, N_s \) are the total number of long, intermediate and short exposures, and \( m, n \) the spatial coordinates.

The thrust of this stage is to assign greater weights to pixels, which represent well-exposed image regions and lower weights to those representing under/overexposed regions in every exposure instance. The distance from the middle value of the Y channel is an indication of well-exposedness of the pixel. Since the transformation RGB-to-YCbCr results to a Y component with range between [16, 235], well-exposed pixels will have values around 128, which is the mean value of the channel, whereas underexposed pixels will obtain values near 16, and overexposed pixels will have values close to the upper bound of the channel, near 235.

Low-luminance regions of the scene are better captured in the overexposed images, compared to any other image of the sequence. As a result, although pixels well-below 128 are not considered to be the well-exposed ones, they are still better in the overexposed images than in any other of the sequence. As overexposed images are treated the ones with mean values greater than 156 and hence their membership functions are selected to be trapezoidal with all pixel values in the interval [16, MVO] to be assigned to maximum membership value i.e. 1, while the pixels above MVO are assigned to lower membership values as they may result to clipping of visual information due to the overexposure. MVO represents the mean value of the overexposed image. Similarly, high-luminance regions are typically better captured in the underexposed images than in any other image of the sequence. As underexposed images are treated the ones with mean values lower than 100, and a trapezoidal membership function is selected, with all pixel values in the interval [MVU, 235] to be assigned to maximum membership value, i.e. 1. In the underexposed images, pixels with values below their mean value are assigned to lower membership values, as they may introduce clipping effects of visual information due to the underexposure. MVU represents the mean value of the underexposed images. These trapezoidal membership functions aim to assign lower weights to the known not well-exposed pixels, i.e. the underexposed pixels in the underexposed images and the overexposed pixels in the overexposed images.

For all images with intermediate exposures, with mean value in the range [100, 156], a trapezoidal membership function is selected, assigning maximum weight to pixels in the range \([\text{min}(MVU), \text{max}(MVO)]\), be-
between the minimum mean value of the underexposed images and the maximum mean value of the overexposed images. Lower weight is assigned to pixels outside this range, which correspond to pixels of under- and overexposed regions, which are better captured in the underexposed and overexposed images as described previously.

2.4 Blending Function and Final Output

The blending process, that follows the assignment of membership functions to the pixels, is performed in two steps in order to form the final fused image. First, all images of the same scale are blended together to form the fused image of the respective scale, which includes all the details of the images that belong to the respective scale, using Eq. (2) for the coarse and fine scales. As a result, we have two fused images, which contain all information in both scales and in the final step these images are blended with the initial color information of the Cb and Cr components to form the final fused image using Eq. (3).

\[ Y_{t}^{\text{out}}(m,n) = \frac{\sum_{k} W_{k}^{t}(m,n) D_{k}^{t}(m,n)}{\sum_{k} W_{k}^{t}(m,n)}, \quad t = \{c, f\} \]  

\[ P_{\text{out}}(m,n) = \frac{\sum_{k} W_{k}(m,n) P_{k}(m,n)}{\sum_{k} W_{k}(m,n)}, \quad P = \{Y_{c}^{\text{out}}, Y_{f}^{\text{out}}, Cb, Cr\}, \]  

\[ k = \{1...N_c, 1...N_f, 1...N_c, 1...N_c\} \]

where, \( c \) is the coarse scale, \( f \) is the fine scale, \( W \) is the pixel weight, \( m \) and \( n \) are the spatial coordinates and \( P \) are the two components Cb and Cr of each exposure and the two fused \( Y \) components, \( D_c \) and \( D_f \) denote the contrast decomposed images at coarse and fine scales, respectively. The aforementioned blending function combined with the membership functions ensures that well-exposed pixels will have greater participation, compared to the under/over-exposed ones. As a result, contrast and visual information of the original scene will be preserved.

In order to obtain a higher contrast image, \( Y_{\text{out}}^{\text{out}} \) is stretched to the interval \([16, 235]\) which are the limits of the YCbCr color space.

Finally, the stretched \( Y_{\text{out}}^{\text{out}} \) component is recombined with the \( Cb_{\text{out}} \) and \( Cr_{\text{out}} \) chromatic components and they are transformed to the final image, using the YCbCr-to-RGB transformation.

3 Comparisons and Discussion

The proposed method has been tested against 9 other state of the art methods, both HDR tone mapping techniques and exposure fusion methods. In the comparison, four of the compared methods are from the two latest versions of commercial HDR software tools, namely Photomatix Pro [13] and FDRTools [14]. Both allow the user to enhance the initial blending process in different ways, such as enhancing color saturation and contrast. In order to perform an impartial evaluation as possible, these extra enhancements of the commercial packages were deactivated, taking only into account the default blending result.

The “Details Enhancer” is a local tone mapping operator and the “Fusion/Natural” is an exposure fusion technique recommended for natural-looking LDR images. Both methods are embedded in the latest Photomatix Pro v.4.2 [13] software and their results are included in the comparison. Both methods “Receptor” and “Compressor”, which are implemented in the latest commercial software FDRTools [14], correspond to a global and a local tone mapping methods, respectively, and their results are also included. The other methods include implementations of Mertens [1], Drago [4], Reinhard [5], Mantiuk [6] and Fattal [7].

Figs. 5, 6 and 7 display comparisons of the proposed method and the other nine methods for the “Coast”, “Water” and “Artificial HDR” scenes, respectively. HDR metrics are used to draw safe conclusions. The HDR metrics used include DRIM (Dynamic Range Independent Image Quality Assessment Metric) [15] which was proposed by Aydin et al. and TMQI [16] (Tone Mapped Image Quality Index) which was proposed by Yeganeh et al. In the evaluation, all tone-mapping methods were compared against the respective HDR image, which was used as reference.

Fig. 5 depicts the exposure sequence of the “Coast” scene and the comparative results of all methods. The proposed method preserves the visual information of the original region better than the methods, that produce clipping of the visual information (Drago [4], Fattal [7], Reinhard [5], Mantiuk [6]) and the methods that loose local contrast producing flat images and wash out colors (“Compressor”, “Receptor”).
Figure 5. Three different exposures for the “Coast” scene and the magnified underexposed and overexposed regions, (a) Proposed method, (b) Details Enhancer, (c) Drago, (d) Fattal, (e) Compressor, (f) Mertens, (g) Fusion/Natural, (h) Reinhard, (i) Mantiuk, (j) Receptor.

Figure 6. Three different exposures for the “Water” scene and the magnified selected underexposed and overexposed regions, (a) Proposed method, (b) Details Enhancer, (c) Drago, (d) Fattal, (e) Compressor, (f) Mertens, (g) Fusion/Natural, (h) Reinhard, (i) Mantiuk, (j) Receptor.

Table 1. Numerical results of “TMQI” metric for HDR scenes. Recall that higher values denote better image quality (Q), better structural fidelity (F) and greater naturalness (N).

<table>
<thead>
<tr>
<th>Algorithm/scene</th>
<th>Coast scene</th>
<th>Water scene</th>
<th>Artificial scene</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Q</td>
<td>F</td>
<td>N</td>
</tr>
<tr>
<td>Proposed</td>
<td>0.98</td>
<td>0.96</td>
<td>0.91</td>
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<tr>
<td>Drago [4]</td>
<td>0.93</td>
<td>0.96</td>
<td>0.59</td>
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<td>Compressor [14]</td>
<td>0.84</td>
<td>0.90</td>
<td>0.19</td>
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<td>Receptor [14]</td>
<td>0.82</td>
<td>0.89</td>
<td>0.13</td>
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<tr>
<td>Mertens [1]</td>
<td>0.98</td>
<td>0.93</td>
<td>0.98</td>
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<tr>
<td>Details Enhancer [13]</td>
<td>0.93</td>
<td>0.95</td>
<td>0.63</td>
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<tr>
<td>Fusion/Natural [13]</td>
<td>0.98</td>
<td>0.95</td>
<td>0.98</td>
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<tr>
<td>Reinhard [5]</td>
<td>0.89</td>
<td>0.93</td>
<td>0.41</td>
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<tr>
<td>Fattal [7]</td>
<td>0.87</td>
<td>0.98</td>
<td>0.25</td>
</tr>
<tr>
<td>Mantiuk [6]</td>
<td>0.92</td>
<td>0.96</td>
<td>0.54</td>
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</table>
Figure 7. Three different exposures for the “Artificial” scene and the selected for magnification region, (a) Proposed method, (b) Details Enhancer, (c) Drago, (d) Fattal, (e) Compressor, (f) Mertens, (g) Fusion/Natural, (h) Reinhard, (i) Mantiuk, (j) Receptor

Table 2. Numerical results of “DRIM” metric. Smaller values denote less contrast distortions. (a) Loss of visible contrast, (b) Amplification of contrast

<table>
<thead>
<tr>
<th>Algorithm/scene</th>
<th>Coast (a)</th>
<th>Water (a)</th>
<th>Artificial (a)</th>
<th>Coast (b)</th>
<th>Water (b)</th>
<th>Artificial (b)</th>
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<tbody>
<tr>
<td>Proposed</td>
<td>0.43</td>
<td>0.03</td>
<td>0.04</td>
<td>0.29</td>
<td>0.06</td>
<td>0.46</td>
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<tr>
<td>Drago [4]</td>
<td>0.79</td>
<td>0.01</td>
<td>0.12</td>
<td>0.13</td>
<td>0.49</td>
<td>0.15</td>
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<tr>
<td>Compressor [14]</td>
<td>0.78</td>
<td>0.01</td>
<td>0.40</td>
<td>0.12</td>
<td>0.09</td>
<td>0.33</td>
</tr>
<tr>
<td>Receptor [14]</td>
<td>0.94</td>
<td>0.01</td>
<td>0.54</td>
<td>0.07</td>
<td>0.44</td>
<td>0.12</td>
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<tr>
<td>Mertens [1]</td>
<td>0.51</td>
<td>0.06</td>
<td>0.13</td>
<td>0.55</td>
<td>0.33</td>
<td>0.43</td>
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<tr>
<td>Details Enhancer [13]</td>
<td>0.45</td>
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<td>0.12</td>
<td>0.30</td>
<td>0.15</td>
<td>0.37</td>
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<tr>
<td>Fusion /Natural [13]</td>
<td>0.23</td>
<td>0.05</td>
<td>0.07</td>
<td>0.39</td>
<td>0.06</td>
<td>0.43</td>
</tr>
<tr>
<td>Reinhard [5]</td>
<td>0.85</td>
<td>0.01</td>
<td>0.16</td>
<td>0.23</td>
<td>0.28</td>
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<td>0.49</td>
<td>0.02</td>
<td>0.06</td>
<td>0.39</td>
<td>0.32</td>
<td>0.14</td>
</tr>
<tr>
<td>Mantiuk [6]</td>
<td>0.76</td>
<td>0.01</td>
<td>0.08</td>
<td>0.09</td>
<td>0.15</td>
<td>0.19</td>
</tr>
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</table>

The proposed method exhibits high scores for both structural fidelity and naturalness, compared to most other methods according to TMQI metric, which is summarized in Table 1. TMQI metric, measures $F$ which denotes structural fidelity, $N$ represents statistical naturalness score and $Q$ is the overall quality measure. Moreover, the suggested algorithm has the least average value of contrast distortions according to the DRIM metric, demonstrated in Table 2 and also has a balance of small values for both loss and amplification of contrast. The smaller the DRIM metric values, the less are the contrast distortions. The suggested algorithm displays high scores for both structural fidelity and naturalness, compared to most other methods. For the “Coast” scene, Details Enhancer algorithm has also high scores for the HDR metrics.

Fig. 6 depicts comparisons for the “Water” scene of the proposed against the other nine methods. Table 1 summarizes the TMQI metric values, for the “Water” scene, where the proposed method outperforms compared to other state-of-the-art tone mapping methods in structural fidelity $F$, naturalness $N$ and overall quality $Q$. Table 2 summarizes the results of DRIM metric, where the proposed method has the least loss of contrast compared to the other methods.

Finally, Fig. 7 depicts the results of the algorithms for an artificial HDR scene, during the CREATE (Colour Research for European Advanced Technology Employment) meeting. The scene includes two simple chambers, one of which is illuminated with a strong directional light, while the other one is not illuminated. Inside the chambers, there is a Macbeth color checker. In this scene, the best results are those of the proposed method and Photomatix Natural Fusion algorithm. The TMQI metric, Table 1, denotes that the proposed method exhibits the highest overall image quality $Q$ and a very high score for both structural fidelity $F$ and naturalness $N$. Finally, the proposed method results to the least loss of visible contrast, DRIM metric, Table 2.

4 Conclusion

We have presented a novel exposure fusion method which successfully blends the initial exposure sequence, preserving visual information and color of the HDR scene. Illumination estimation is used for contrast decomposition of the original images of the exposure sequence and also to provide information about whether a region is under- or over-exposed. Membership functions are used to assign greater degree of participation to the “well-exposed” pixels of the contrast decomposed images and lower to the rest pixels. As a result, well-exposed pixels contribute more to the fi-
nal image, than the other pixels. Moreover, although pixels that represent underexposed and overexposed regions are not considered as the well-exposed ones, they still contain more visual information in the extended and the shortest exposure images and are assigned to maximum participation in the membership functions. Membership functions are applied to the contrast decomposed images and the weights of pixels are generated according to the illumination estimation of the same frequency. All pixels of the images representing the same frequency are blended according to their weights and finally both images of the fine and coarse scales are blended to form the final image. Experimental results prove that the proposed method outperforms current well-known methods by using both LDR and HDR metrics. The DRIM metric was used in the comparisons and proved that the proposed method preserves original contrast information better than the other methods. The proposed method outperforms other similar algorithms in preserving better structural, luminance and chrominance fidelity of the scene for both underexposed and overexposed regions according to the TMQI metric. A number of applications, such as HDR photography and HDR displays, where fusing differently exposed images is required, can benefit from the proposed technique.

References


