Contrast Enhancement Based on a Morphological Rational Multiscale Algorithm

Mejora de Contraste Basada en un Algoritmo Morfológico Racional Multiescala

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Abstract. Contrast enhancement is an important task in image processing and it is commonly used as a pre-processing step in order to improve the results for other tasks such as segmentation. However, not only do some methods for contrast improvement have good performance working on low contrast regions, but they also affect good contrast regions; owing to the fact that some elements could be vanished, representing a loss of information. A method focused on images with different luminance conditions is introduced in the present work. The proposed method is based on morphological filters by reconstruction and rational operations, which together, allow a uniform contrast enhancement. Furthermore, due to the properties of these morphological transformations, the creation of new elements on image is avoided. The processing was made on luminance values in the u′v′Y′ color space, which permits to keep the chrominance and to avoid the creation of new colors. As a result of the previous considerations, the proposed method keeps the natural color appearance of the image.
Keywords: Contrast enhancement, Rational operations, Morphological filters, Mathematical morphology.

Resumen. La mejora del contraste es una tarea importante en procesamiento de imágenes y a menudo es usada como paso de pre-procesamiento a fin de mejorar los resultados de procesos como segmentación. Algunos métodos para mejora de contraste tienen un buen desempeño trabajando en regiones con poco contraste pero también afectan las regiones con suficiente contraste; este es un efecto no deseado debido a que algunos elementos de la imagen pueden ser eliminados lo cual representa una pérdida de información. En este trabajo se presenta una mejora de contraste enfocada a imágenes que tienen diferente luminancia sobre la misma escena. El método propuesto está basado en filtros morfológicos por reconstrucción y operaciones racionales, que en conjunto permiten una mejora de contraste uniforme. Además, debido a las propiedades de estas transformaciones morfológicas se evita la creación de nuevos elementos. El procesamiento trabaja sobre los valores de luminancia en el espacio de color u′v′Y′, lo cual permite mantener el croma y evitar la creación de nuevos colores. Como resultado de las consideraciones mencionadas, este método provee una mejora de contraste uniforme y mantiene la apariencia natural de la imagen.
Palabras clave: Mejora de contraste, Operaciones racionales, Filtros morfológicos, Morfología matemática.

1 Introduction

Nowadays, image processing is applied in many areas and on a wide variety of images. Images are taken under diverse conditions and in different environments. Many factors as shadows and illumination affect the image and particularly in an outdoor scene; it is even more affected by its surrounded context. Contrast is the characteristic that permits a better discrimination among regions and elements on a scene, and it is frequently affected by luminance conditions. For example, if an image is taken under a weak light condition the contrast among its elements will be low; an image in this condition cannot provide enough information for the correct interpretation of the scene in a further process. In tasks as segmentation and classification, where a parameter value (such as luminance or color) is used for distinguishing one element from another, a good contrast could be helpful in order to improve the results and make image understanding easier. So, if images with low contrast require a pre-processing step aim to prepare them for further processes, it is necessary to develop efficient tools for this purpose.

Methods for image enhancement can be classified into spatial and frequency domain methods; the present work is focused on the spatial domain based on mathematical morphology. This type of method works directly with pixels and it could be done in two ways: either by processing each pixel individually (negative, thresholding, equalization) or by taking information of the neighboring regions (Retinex) (Land and McCann, 1971). The latter way is certainly more interesting because it works in a similar mode as human visual system, which takes into account the influence of neighboring regions for defining a new region or object. The improvement of contrast in mathematical morphology is based on a concept proposed by Kramer and Bruckner (1975), which consists on comparing each image pixel with two different patterns (for example, eroded and dilated images) and taking the closer value to the original image. An analysis to this concept was made by Serra (1988), where the author introduces the toggle mappings notion and shows that the use of patterns such as the erosion and the dilation could degrade the image. Later, Meyer and Serra (1989) improve the toggle-mapping idea using idempotent transformations, which avoid image degradation. The contrast theory for mathematical morphology arises based on this new concept and some morphological methods have been developed since then. Toet (1992) proposed a multi-scale image decomposition based on a ratio low-pas pyramid. This scheme is very similar to that of the popular difference of low pass or difference of Gaussian pyramid structures. A first version of this approach is proposed by Toet (1990) using alternating sequential morphological filters. These morphological filters play the role of low pass filters. Terol-Villalobos (1995, 1996) proposed the morphological slope filters as contrast operators, which are non-increasing filters and are based on gradient and idempotent mapping criteria. Slope filters attenuate low contrast regions and keep high contrast regions; thus, high contrast regions are more noticeable owing to the attenuated regions. Mendiola-Santibañez and Terol-Villalobos (2002, 2005) proposed a contrast enhancement based on the measurement of contrast difference into an images set; these values were graphed against two parameters (α and β), which varied in the close interval [0, 1] . The global maximum and minimum values with greater altitude are associated with an image with good visual contrast. Mukhopadhyay and Chanda (2000) proposed a multi-scale contrast enhancement using top-hat operators; its main advantage is the possibility of working with dark and light regions in gray level images. Recently, Espino-Gudiño et al. (2007) studied the opening by reconstruction on rational operations and its use as contrast operator; this method works with color images and achieve good results improving contrast on dark regions.

As we can see there are methods for improving the contrast in mathematical morphology; however, the improvement not only depends on the method but also on the image characteristics. For example, it would be interesting to get to know the result of applying a method which improves the contrast on dark regions over an image with light regions. Some contrast enhancement methods are focused on improving dark regions owing to invisibility of the elements of those regions, and as a consequence, the element on light regions could be vanished or have an unnatural appearance. Nevertheless, images with low contrast are not always predominantly dark or light; they also combine both conditions. Some other methods avoid vanish elements but change the chromatic appearance or make some regions look faded. The proposed method is focused on images with different illumination conditions; it is derived of the multi-scale process proposed by Espino-Gudiño et al. (2007). The novelty of this method consists on the use of multi-scale rational operations but combining the results of openings and closings by reconstruction, which ensures that each region on image will be reached. Furthermore, this method also keeps away from changing the chrominance values because it works only with the luminance intensity. In this way, the final image presents a global enhancement without affecting those regions that already had good contrast and without creating new colors.

2 Basic Concepts

2.1 Mathematical Morphology

A morphological filter is an increasing and idempotent transformation (Serra, 1982; Soille, 2003); former characteristic means that the order must be preserved and latter characteristic states that a transformation Ψ is idempotent if and only if $\Psi[\Psi(f)]= \Psi(f)$ for all image f. Opening and closing (1) transformations are basic filters on mathematical morphology and they are denoted as $\gamma_{\mu B}$ and $\varphi_{\mu B}$, respectively; where B is the basic structural element formed by a square of 3x3 pixels containing the central pixel and μ is a scalar; thus, μB is a structuring element of size $(2\mu+1)\times(2\mu+1)$. These basic filters are composed by the basic transformations in mathematical morphology called erosion (ε) and dilation (δ); these transformations are defined as $\varepsilon_{\mu B}(f)(x)= min\{f(y);\ y\in \mu B\}$ and $\delta_{\mu B}(f)(x)=max\{f(y);\ y\in \mu B\}$, where *max* and *min* are the maximum and minimum value, respectively. Erosion and dilation are transformations that permit to eliminate or to remark present structures on the image according to the size of transformation. Nevertheless, these modifications in the original structures are an undesirable effect in image processing. Moreover, both transformations are not idempotent, but its combination is the origin of majority filters and transformations in mathematical morphology.

$$\gamma_{\mu B}(f)=\delta_{\mu B}[\varepsilon_{\mu B}(f)] \text{ and } \varphi_{\mu B}(f)=\varepsilon_{\mu B}[\delta_{\mu B}(f)] \qquad (1)$$

Other filters based on basic transformations are the filters by reconstruction or geodesic filters (Vincent, 1997; Lantuéjoul and Maisonneuve, 1984). These filters are built by iterating until stability the basic geodesic dilation and erosion defined as $\delta_f^1(g)=f\wedge\delta_B(g)$ with $f\geq g$ and $\varepsilon_f^1(g)=f\vee\varepsilon_B$ with $f\leq g$, respectively. Where g is the marker frequently computed from the reference image f. Particularly, when the marker image g is given by the morphological erosion or dilation of the reference image the opening and closing by reconstruction (2) are obtained. When a filter by reconstruction is applied, the marker grows inside the reference image by preserving the shape of the reconstructed elements.

$$\tilde{\varphi}_{\lambda B}(f)=\lim_{n\to\infty}\varepsilon_f^n[\delta_{\lambda B}(f)]=\underbrace{\varepsilon_f^1\varepsilon_f^1\ldots\varepsilon_f^1}_{\text{Until stability}}[\delta_{\lambda B}(f)]$$

$$\text{and} \qquad (2)$$

$$\tilde{\gamma}_{\lambda B}(f)=\lim_{n\to\infty}\delta_f^n[\varepsilon_{\lambda B}(f)]=\underbrace{\delta_f^1\delta_f^1\ldots\delta_f^1}_{\text{Until stability}}[\varepsilon_{\lambda B}(f)]$$

Remark: B could be omitted because its size is constant, thus the expression $\varphi_{\lambda B}$ is the same as φ_λ. In the same way if $\lambda=1$ then the expressions $\varphi_{\lambda B}=\varphi_\lambda=\varphi$ are equivalents.

Kogan et al. (1998) developed other filters called morphological rational filters, which are a combination of the morphological basic transformations (erosion and dilation) for improving border detection. This study is the basis of the morphological rational contrast method proposed by Espino et al. (2007). Their method consists on applying a rational operation between the image and its opening by reconstruction. Furthermore, they proposed a multi-scale process (3) where the opening at scale μ_{n+1} is used as background in order to detect and improve regions at scale μ_n. Multi-scale process takes into account the quantitative relation between the magnitude of physical stimuli and its perception, established by Weber's law. This law establishes that the necessary increment, of the stimulus intensity in order to generate a change in the sensation, is proportional to the intensity of the original stimulus. Regarding this fact, the multi-scale process uses openings by reconstruction that permits to generate a noticeably enough change for improving the image. So, by using multi-scale rational filters (MRF) it is possible to enhance the contrast.

$$R_M(x,\mu)=\sum_{n=1}^{N}\frac{\tilde{\gamma}_{\mu_{n-1}}(f)(x)}{\tilde{\gamma}_{\mu_n}(f)(x)} \ \text{with} \ \tilde{\gamma}_{\mu_0}(f)=\tilde{\gamma}_0(f)=f \qquad (3)$$

2.2 Multi-scale Retinex

Retinex was the first attempt to develop a computational model in order to emulate the process of human vision (Land, 1986; Land and McCann, 1971). This method improves the visual representation of images when light conditions are not good (Rizzi et al., 2004; Rahman et al., 2004) and it is based on the biological mechanism of human eye. The algorithm is based on the estimation luminance of a point influenced by N points. Multi-scale Retinex is an adaptation from original Retinex combining the result of n individual processes (Barnard and Funt, 1999) expressed by equation (4). R_i is the result of processing f with N scales and it is given by the weight (w) of each individual process multiplied by the logarithm of the ratio between f and the convolution (*) of f with a Gaussian function $F(x,y,c)=Ke^{-(x^2+y^2)/c^2}$, where c is the scale. Multi-scale Retinex (MSR) is widely used for contrast improvement on dark images and have some similarities with MRF such as both consider the neighbor information for improvement and both separate luminance from reflectance.

$$R_i(x,y,w,c) = \sum_{n=1}^{N} w_n \log \frac{f(x,y)}{F(x,y,c) * f(x,y)} \qquad (4)$$

2.3 Color spaces

Digital images are often represented on RGB color space (red, green and blue); this space has been widely used owing to its facility of representation in electronic devices for exhibition of images (monitors, t. v. screens, projectors, etc.). RGB is an additive color space because it is possible to obtain a wide color gamut by mixing red, green and blue in different quantities (Süsstrunk et al., 2001; Fairchild, 2005). According to the International Commission of Illumination (CIE), *brightness* is the quantity of light produced by a source, and *luminance* is the radiated intensity which impacts to human eye. It means, luminance that we perceive is what permits us to distinguish if a color is brighter o darker than other. In RGB space it is not possible to have direct access to luminance values; in this way, if original values change not only could they be saturated or desaturated, but a different new color could be created. This is the main reason why when luminance needs to be manipulated, it is necessary to translate information at another color space.

There are color spaces that take other parameters for color representation, like HSL space (*Hue, Saturation and Luminance*), HSV space (*Hue, Saturation and Value*) and HSI (*Hue, Saturation and Intensity*) (Fairchild, 2005; Smith, 1978; González and Woods, 1992; Levkowitz and Herman, 1993). In recent years, new color spaces, which work more according to the natural way of human vision and have a uniform perception, have been proposed. The uniform perception is an important characteristic in color spaces and it refers to the fact that the intensity of a change in a color must produce the same perceptual difference in any other. For example, on the XYZ color space, the distance between two tones of green must be significant enough for producing a perceptual difference. Nevertheless, if the same increment is applied on two tones of red, the perceptual difference is major because on red region a shorter distance between the tones implies a more significant difference with respect the green region. It means that the XYZ color space is not perceptually uniform. When the goal is image improvement, this characteristic is imperative because it involves enhancing some regions without affecting others. Color spaces perceptually uniform have a high use in image processing. Yet, CIE recommends two: L*u*v* and L*a*b* (L*=luminance and chrominance=u*, v*, a*, b*) (Hanbury and Serra, 2002; Pei et al., 2004). The space u'v'Y, similar to L*u*v*, was proposed by Lucchese and Mitra (2004) and it permits to have chromatic (u'v') and achromatic (Y) information of image. Thus, it is possible to process the chromatic values, in order to saturate or desaturate, using the gravity center law (Hunt, 2001); thus, when the position of a point is located, this can be moved in some proportion to the red, yellow, green, cyan, blue or magenta according to the weight of its gravity center. In this way a color can change the intensity of its chrominance without creating a new color. Transformation matrices permit to change image values from one space to another with its equivalent values. In order to improve luminance but keeping the original chrominance of a color, the u'v'Y color space will be used in the proposed method. Therefore, it is necessary to translate de RGB values to u'v'Y values using its corresponded transformation matrix (5).

$$\begin{bmatrix} Y \\ u \\ v \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ -0.147 & -0.289 & 0.436 \\ 0.615 & -0.515 & -0.100 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \qquad (5)$$

3 Proposed Method

When an image shows a complex illumination condition with dark and light regions, it is more difficult to carry out a good improvement. On the one hand, if the enhancement is focused on dark regions then light regions could be saturated or even vanished; on the other hand, if light regions are improved the change could be little noticeable on dark regions. The objective is to find an equilibrium which permits a general contrast enhancement in this kind of images. In this work a combination of multiscale processes with openings and closings by reconstruction is proposed. Rational operations using openings (3) improve dark regions and using closings (6) improve those regions untouched by openings.

$$R_{M\varphi}(x,\mu)=\sum_{n=1}^{N}\frac{\tilde{\varphi}_{\mu_n}(f)}{\tilde{\varphi}_{\mu_{n-1}}(f)}\;\; con\;\; \tilde{\varphi}_{\mu_0}(f)=\tilde{\varphi}_0(f)=f \qquad (6)$$

Thus, a complete improvement of image is carried out when rational operations with both transformations are applied. The process consists on applying the required scales of the image, so the first step is to find the corresponding scales for each filter.

3.1 Scales Determination

Size and scale are intrinsically linked. Scale links the size of the regions to a representation of the image. In many circumstances, the regions of interest to be detected in order to contrast them belong to different scales, then a series of coarser and coarser representations of the same image are derived. A multiscale representation will be completely defined if one has defined the transformations from a finer scale to a coarser scale. In linear filtering, the operator for changing scale is a convolution by a Gaussian kernel and its major utility is to regularize images. Besides several advantages, this linear approach has several disadvantages. For example, after convolution with a Gaussian kernel the images are blurred, particularly some regions of interest like the edges. Moreover, the localization of the structures becomes imprecise in particular at large scales. Other nonlinear multiscale approaches consider the evolution as a function of their geometry avoiding these drawbacks, among them the morphological approaches have a great interest in image processing. Between the different morphological multiscale tools the openings and closings by reconstruction are powerful transformations that preserve edges. To carry out a multiscale representation, many scales could be applied in a transformation but depending on the image, just some of them imply important results. The importance of knowing those scales is with the aim of identifying the most significant scales that best represent the structures of the image, which can be translated in a short processing. The traditional tool in mathematical morphology to study the scales or sizes of the structures in the images is called granulometry by openings. Granulometry, a concept formalized by George Matheron in the binary case (Matheron, 1967) and extended by Serra (1988) to the gray-level case, is used as a tool aiming at classifying structures according to a series of sieves. To classify them according to their size means to define a family of transformations $\{\Psi_\lambda\}$ depending on a positive parameter $\lambda \geq 0$. These transformations must be: (a) Anti-extensive, which means for a given λ, that the structures greater than λ form a subset of the original structures, (b) Increasing expressing that a subset, for example structures greater than λ, are a part of all structures greater than λ, and (c) the stronger property $\Psi_\lambda\Psi_\mu = \Psi_\mu\Psi_\lambda = \Psi_{\sup(\lambda,\mu)}$. This last condition is a little more subtle than the preceding ones and it expresses that sieving the structures by using to sieves of sizes λ and μ gives the same result than sieving the structures by the greatest sieve. Observe that granulometry makes reference to the characterization of the elements size present on image; its application on mathematical morphology is based on consecutive morphological transformation with incremental size of λ (Matheron, 1975; Serra, 1982; Dornaika and Zhang, 2000; Vincent, 2000). Since the openings with convex structuring elements satisfy these axioms a granulometry can be simply defined as a decreasing family of openings.

Definition1: *A family of openings* $\{\gamma_\lambda\}$, *where* $\lambda\in\{1,\ldots,n\}$, *is a granulometry if for all* λ, $\mu\in\{1,\ldots,n\}$ *and all function* f, $\lambda \leq \mu \Rightarrow \gamma_\lambda(f) \geq \gamma_\mu(f)$.

Moreover, granulometries by closings, also called anti-granulometries, can be defined as families of increasing closings and they are used for analyzing dark structures. The granulometric analysis provides information about how much the size λ affects the image. Performing the granulometric analysis of an image f is equivalent to mapping each opening size λ with a measure of the opened image $mes(\gamma_\lambda(f))$. This measure is chosen to be the area or the volume. Therefore, granulometric curve or also called pattern spectrum of f is then defined as the arithmetical difference $PS_\lambda(f) = mes(\gamma_\lambda(f)) - mes(\gamma_{\lambda+\Delta}(f))$. When $\Delta = 1$, the function $PS_\lambda(f)$ maps each size λ to some measure of the bright image structures with this size, whereas for $\Delta > 1$ structures with size between λ and $\lambda + \Delta$ are mapped at each size λ. In order to know the portion of structures of size λ contained in the image $PS_\lambda(f)$ is normalized by the measure of the original image $(mes(f))$.

Then, equation (7) expresses the granulometric process using openings, *mes* is the volume measure of the image and

$$G(\lambda) = \frac{\text{mes}(\gamma_\lambda(f)) - \text{mes}(\gamma_{\lambda+\Delta}(f))}{\text{mes}(f)} \tag{7}$$

$G(\lambda)$ is the granulometric density function. The volume measurement (*mes*) is defined as the sum of all the pixel values of an image. In this case the interesting data are the values of density function with the highest values because these suggest the most accurate λ values for f. It is important to clarify that although most of the images need a multiscale process, it is also possible that one single scale provides the best result and this depends on each image. Granulometry by closings uses a similar expression.

3.2 Combined Multi-scale Rational Filters

As aforementioned the main idea is to combine the best of both multiscale processes (Equations (3) and (6)) in a single final image. In this way, one filter works improving a region with luminance A and as a possible consequence could fade away elements of other region with luminance B, but those elements are not lost because they are conserved by the dual transformation; so when both results are combined, in the accurate proportion into one final image, the result is a uniform contrast improvement. The proposed approach to produce a contrast enhancement consists in constructing a joint multiscale rational method of openings and closings. Once both output images $R_{M\gamma}$ and $R_{M\varphi}$ are available, it seems obvious that we can combine them to obtain the called *combined multiscale rational filter* (combined MRF). Among the different alternatives for the combination, a barycentric linear combination of both images is carried out. In mathematical terms, we have:

$$F_{final} = R_{M\gamma}a + R_{M\varphi}b \tag{8}$$

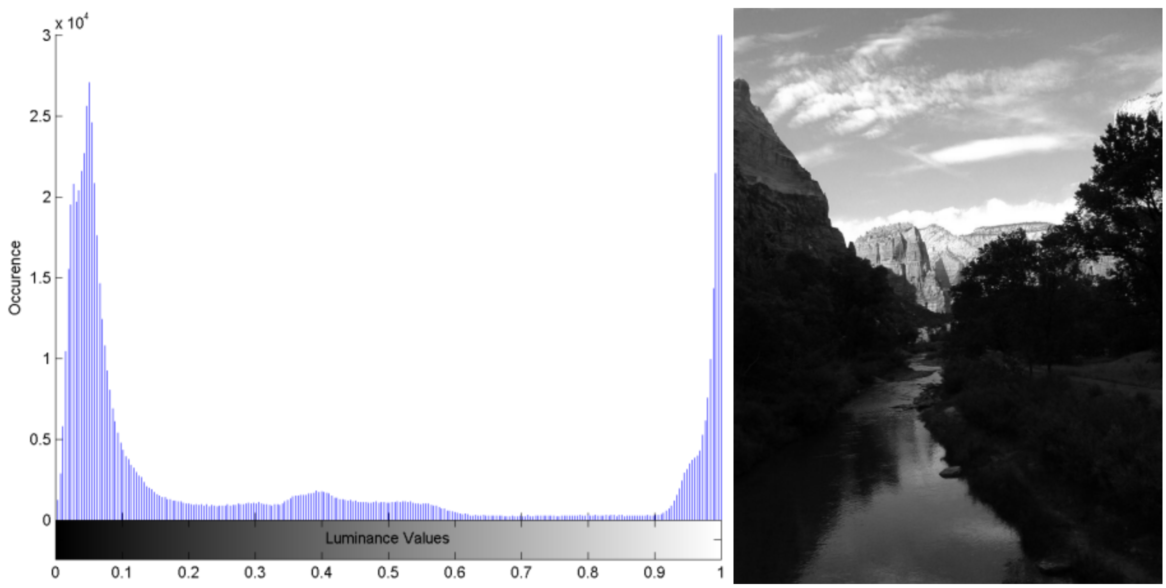
Where $R_{M\gamma}$ and $R_{M\varphi}$ are the results of rational operations, a and b are the assigned percentages, which add together 1.0, and F_{final} is the final result that contains the contrast enhancement. Since both rational filters are based on transformations by reconstruction they conserve their characteristics without affecting original structures; this makes the combined MRF reliable.

4 Experimental Results

Consider the case of Fig. 1 (a,b), where the image shows two different light conditions. On the one hand bright region has a good illumination and it is possible to observe clearly its elements; on the other hand it is quite difficult to observe the content on the dark region and even more difficult to determine the limits among its elements. The histogram helps to have a better understanding about luminance distribution on this image; notice that there is one peak in the lowest values and another in the highest values, which represent the two predominant regions (dark and light). Image does not have a uniform distribution in its luminance and this causes a poor contrast; so, an image in this condition cannot provide enough information to other processes. In order to uniform the luminance distribution a contrast enhancement is necessary.

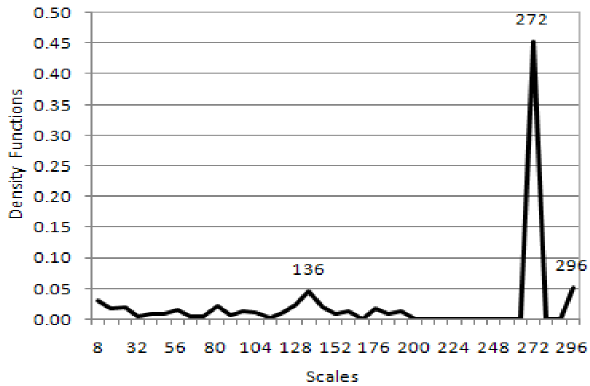
Step 1: A granulometric analysis is applied to Fig. 1(b) with the aim to find the most accurate scales for it. The analysis was made incrementing the scales in Δ=8 (see equation (7)) until a maximum of λ=300. The most representative values on resulting graphics indicate the size of those scales that work better with its corresponding filter (Fig. 2 (a, c)). For opening, three scales are the most relevant, but the best result was obtained with λ=296. MRF with opening works improving light regions (Fig. 2 (b)), in this case the image has enough contrast in that region and the change is little noticeable; so, the objective to apply the filter is to conserve and to remark its elements for final image. MRF with closings works in the improvement of dark regions; the granulometric analysis for the closings shows several important scales which were tested, resulting λ_1=144 and λ_2=224 the most accurate combination. It is important to observe that some elements on light region have disappeared; however, these elements are not lost because they were conserved on the opened image. The change made by MRF with closings is pretty noticeable (Fig. 2 (d)) due to the fact that dark region suffers the most dramatic improvement.

Step 2: If resultant images are used individually, although they can show a noticeable contrast enhancement in some regions, this result will not be uniform. So, they were combined in different proportions resulting $a = 0.6$ and $b=0.4$ the more accurate percentages. The new histogram permits to understand how luminance was better distributed along of a valid range (Fig. 3(a)). Change is evident on resulting image (Fig. 3(b)) where now it is possible to distinguish among elements on dark regions; furthermore, regions with enough contrast were not changed drastically but they were slightly improved. The combination of both filters permits a better appreciation of global improvement, where there can be a better understanding of the importance of considering the neighbor information; changes result natural for the observer because they have a certain harmony with the environment around them.



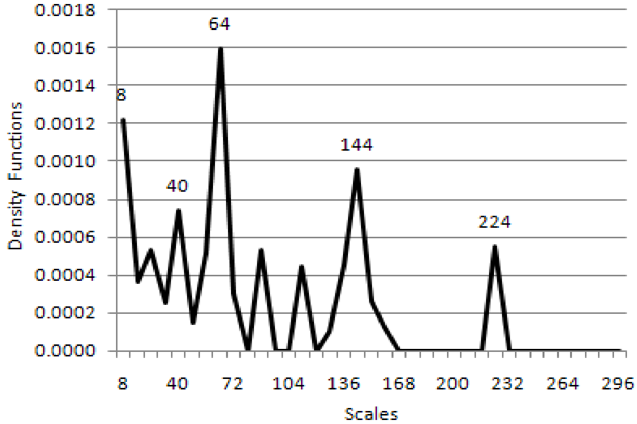
(a) (b)

Fig. 1. (a) Luminance distribution of (a) an image with different lighting conditions



(a)

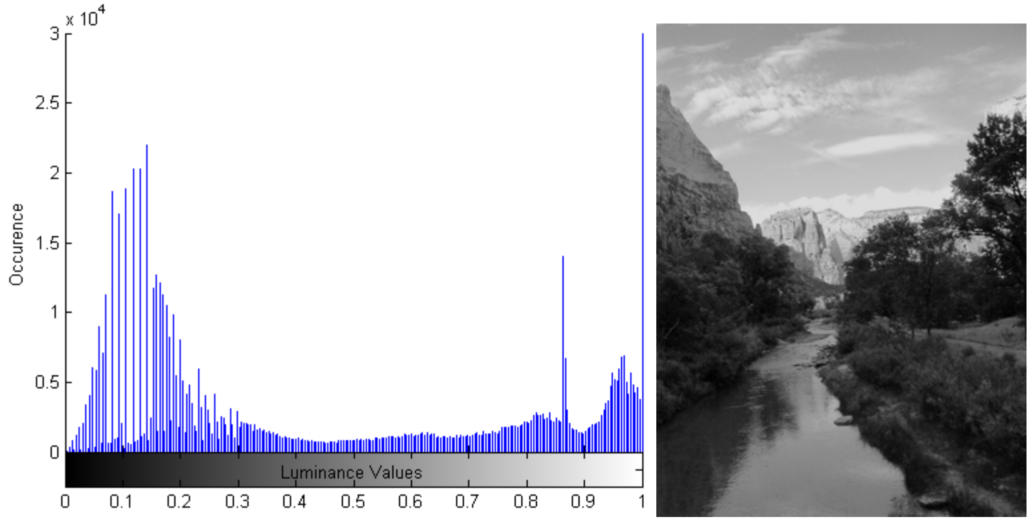
(b)



(c)

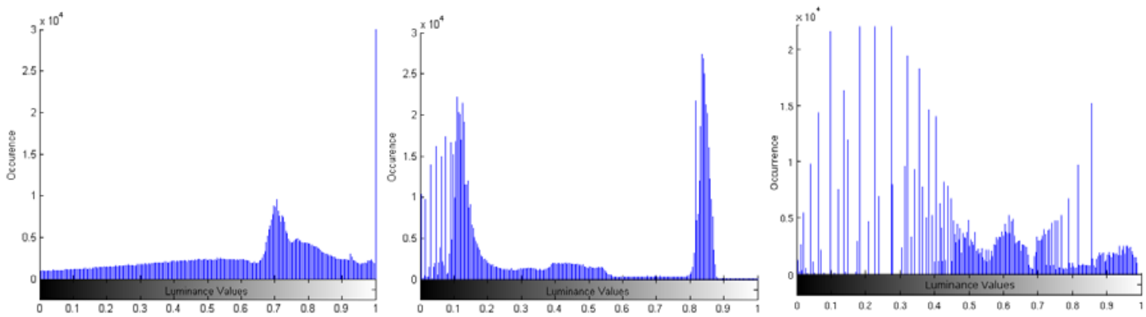
(d)

Fig. 2. Granulometric analysis with openings and closings (a, c) and its respective application on MRF (b, d)



(a) (b)

Fig. 3. Combined MRF (a) luminance distribution and (b) resulting image



(a) (b) (c)

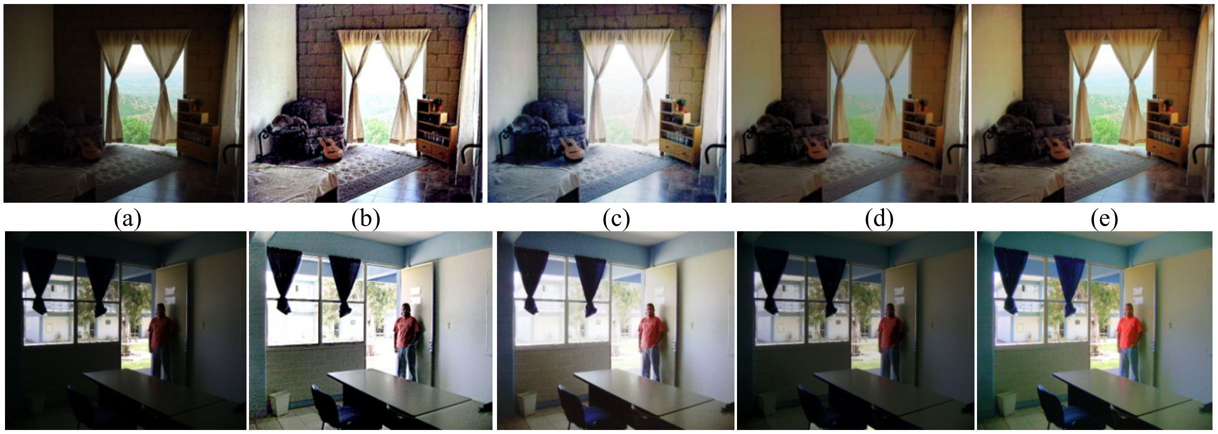
Fig. 4. Luminance distribution on contrast improvement results by (a) MSR, (b) MRF with openings and (c) equalization

Comparative: With the aim of having a better appreciation of the results, these were compared with three previously mentioned methods: MSR, MRF with openings and equalization. Figure 4(a) shows the luminance distribution resulting from a contrast enhancement by MSR. The two peaks were attenuated and values have better distribution now; it is evident that many values were moved closer at higher values causing more light regions. However, as it can be observed on its color result (Fig.5(b)), contrast is higher in dark regions but also regions with good contrast, on original image, were affected making them grayish. Color was also affected, not only on intensity but also in a drastic change of chrominance values; this leads to an unnatural appearance by the creation of false colors. On the other hand, MRF with openings shows a contrast enhancement, mainly on the higher values (Fig. 5(c)), although the majority of pixels are still concentrated on two opposite sides (Fig. 4(b)). Three scales were used for MRF with openings λ_1=296, λ_2=356 and λ_3=416; however, as only one transformation is used, some regions look faded. Particularly in this image, it is not possible to reach a better result by MRF with openings; it keeps the chromatic appearance closer to the original colors due to the luminance was worked on the space u'v'Y. Equalization improvement distributes image values all the valid range along (Fig. 4(c)) which permits a better discrimination among regions. Yet, this result is not accurate because there are two specific regions that must be distributed. There is also a wide region the values of which must be preserved; equalization does not consider the region characteristics but distribute all the values then some regions are improved and others are affected (Fig. 5(d)). Finally, Fig. 5(e) shows the image computed by the combined MRF; the process improves the luminance values making darker or lighter the color but without changing the chrominance. Colors present a natural change caused by the new luminance values, but the original chrominance was preserved. Thus, final image gets a global and uniform contrast enhancement and also it keeps a natural appearance. Other results and its comparative are shown on Fig. 6.

(a) (b) (c) (d) (e)

Fig. 5. (a) Original image and its improvements by (b) MSR, (c) MRF with openings, (d) equalization and (e) combined MRF on color

The importance to compare those methods is because color resulting images permit a visual comprehension about the difference among methods and to demonstrate how the improvement achieved with openings can be improved even more if it is complemented with closings (and viceversa). This combination allows a complete enhancement in terms that its individual work is complemented with the dual transformation work. Some increasing transformations, such as the morphological openings and closings, could modify the original image structures when they are applied. In mathematical morphology, it is possible to reconstruct these structures through the reconstruction transformations. The main advantage of the reconstruction transformation consists on not adding new elements. Openings and closings by reconstruction are used on combined MRF; in this way, it is viable to ensure that just the original elements and forms are restored on the final image. Also, by using a structural element on mathematics morphology it is possible to reach a better approximation of the human visual compensation under light changes.



(a) (b) (c) (d) (e)

(f) (g) (h) (i) (j)

Fig. 6. (a, f) original images and its contrast enhancement by (b, g) MSR, (c, h) equalization, (d, i) MRF with openings and (e, j) combined MRF on color

5 Discussion Cases

Although the main case of study is an image with illumination dynamics as Fig. 5, it is important to know how this method works with other kind of images. By the similitude between MSR and combined MRF only these methods are compared on next cases.

5.1 Dark images

Consider Fig. 7(a) which shows a low contrast caused by a poor illumination condition. Its luminance histogram (Fig. 7(d)) has most of the values over the darkest region; so with the purpose of improving the image, the values must be better distributed. MRF with openings alone works light regions. Therefore, in this case it does not result accurate; however, it could provide strong structures for final image if it is used by combined MRF. Image was firstly processed with MSR and the output image presents an important enhancement since its distribution throughout the luminance range (Fig. 7(e)). The new distribution effect is observed on Fig. 7(b) in which an easier discrimination among elements is possible; the change of some colors is also a consequence of the applied processing. The tested results of granulometric analysis suggest the scales $\lambda1=104$ and $\lambda2=120$ for openings and $\lambda1=156$ and $\lambda2=172$ for closings. By using combined MRF, not only do luminance values have a good distribution but also colors were conserved in the output image (Fig. 7(c, f)).

5.2 Good condition images

An important characteristic about the enhancement methods is how they work over an image in good conditions. For example, if a set of different images is processed, under a contrast enhancement method, the ideal result would be that those images with low contrast are improved but those with good contrast keep this condition. Latter form was tested in order to know how the proposed method works and how its result is respect to other method. Fig. 8(a) shows an image with good contrast, according to its luminance distribution (Fig. 8(d)), in which one element is sufficiently distinguished from the other, so a contrast improvement is not necessary. Distribution is more homogeneous along the luminance range when MSR is applied; yet, its effect in color is little satisfactory because the colors are oversaturated on final result (Fig. 8(b, e)). According to the granulometric analysis the applied scales with the greatest impact are $\lambda1=100$ for opening and $\lambda=60$ for closing. Combined MRF change the luminance distribution although it is closer to original, then color is affected minimally (Fig. 8(c, f)). Hence, by combined MRF it is possible processing an image amid good contrast conditions without affecting it on significant way either resulting on an unnatural appearance.

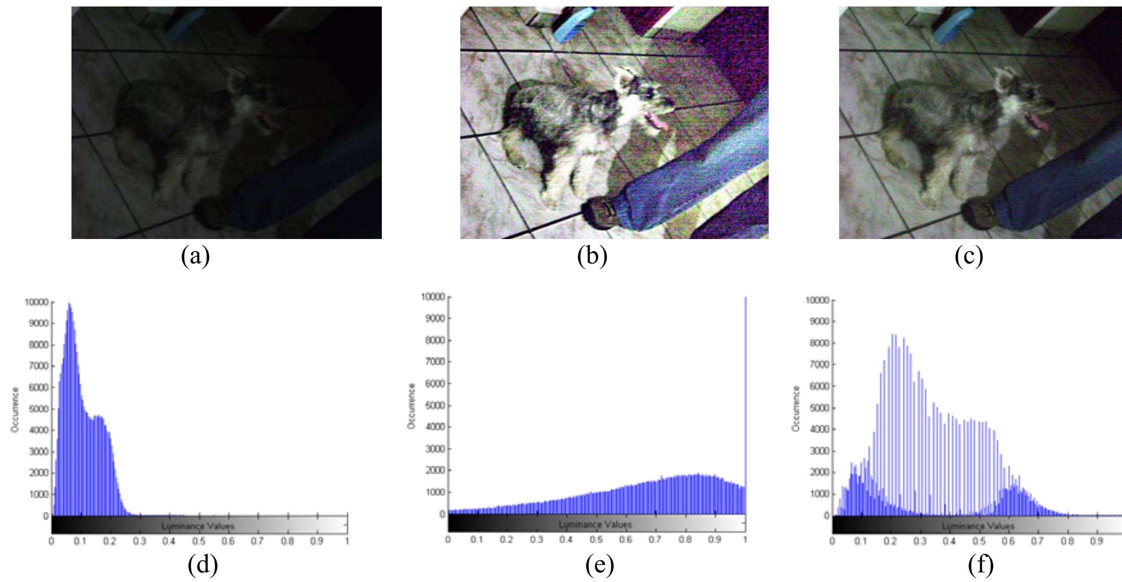


Fig. 7. (a) Original dark image and its improvement by (b) MSR and (c) combined MRF with their respective luminance distribution (d, e, f)

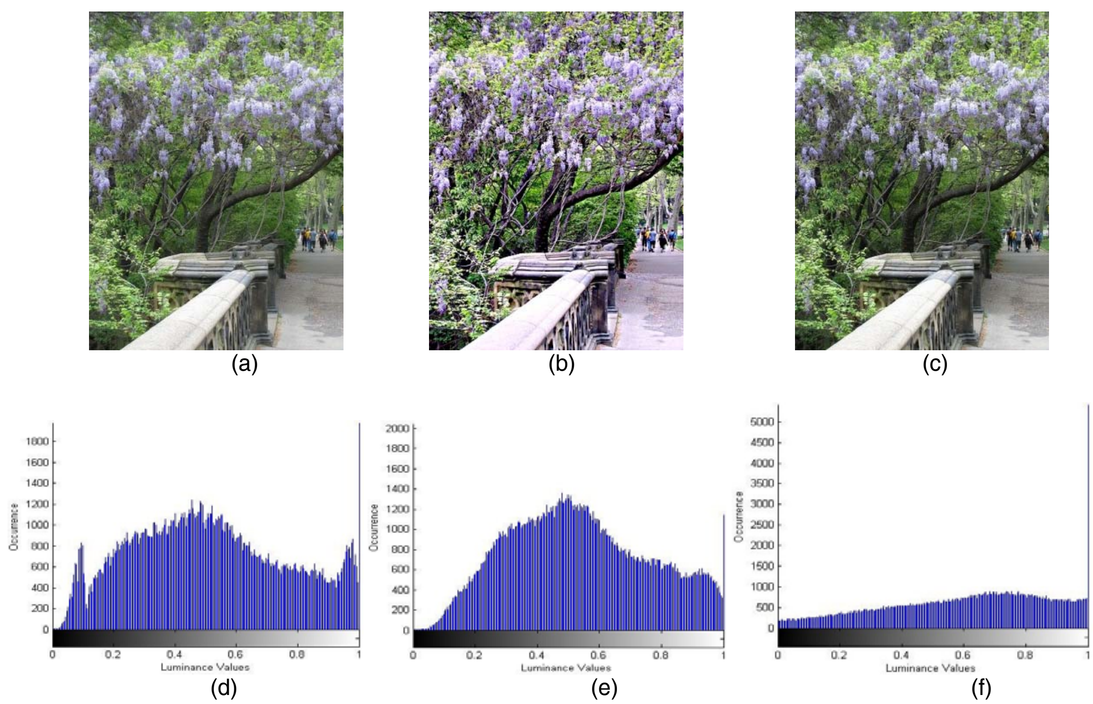


Fig. 8. (a) Original image with good contrast and its improvement by (b) MSR and (c) combined MRF with its respective luminance distribution (d, e, f)

6 Time Evaluation

Time evaluation, in this study case, depends on many parameters as image size, number of MRF by openings and by closings and their respective sizes. So, it is not possible to determine in a general way a specific range of time for this process. Yet, it is important to have an idea of the processing time for combined MRF in order to evaluate its performance. Table 1 shows the processing time of the images presented in this work and its processing information according to its processing characteristics. Combined MRF was implemented using C language on a Centrino PC with a clock speed of 1.73GHz, 80GB HD, 1GB RAM under Linux platform.

Table 1. Time evaluation of Combined MRF

Image	Size	MRF with Openings	MRF with Closings	Processing Time
Fig. 1(b)	768x1024	296	144, 224	46.8s
Fig. 6(a)	640x480	75, 136	144	10.5s
Fig. 6(f)	640x480	144, 152	52	10.8s
Fig. 7(a)	640x480	104, 120	156, 172	15.2s
Fig. 8(a)	375x500	100	60	3.0s

7 Conclusions

Enhance the image contrast is a complicated task when different illumination conditions affect it. There are methods which provide a good improvement but they alter the original colors resulting on an unnatural appearance. In this work the morphological filters and rational operations were studied with the aim to apply them for contrast improvement. The proposed method permits to get a better contrast, without creating new structures or modifying the existing. It is based on rational multi-scale operations with openings and closings by reconstruction; thus, by combining both results in some percentage a uniformly improved image is obtained.

This method works over the luminance, in a color space closer to natural human vision, and its goal is to improve it but taking its neighborhood into consideration; besides, this avoids the creation of false colors. It means that there is a change in intensity not on original hue; this in turn permits to keep a natural appearance. As it was shown, combined MRF improves an image but affecting in a little proportions those regions with good contrast. Predominantly dark images can be processed with the same method and it is possible to achieve good results; moreover, even when the whole image has good contrast, and it is processed under this method, the result shows a low significant change. The last case is an important characteristic about combined MRF because it does not affect the good state of image in a negative way. Other characteristics about the proposed methods are being investigated.

It is important to clear out two issues: the presented method is focused on contrasting enhancement and keeping the original chrominance. Nevertheless, after some processes, like contrast enhancement, colors could result faded or oversaturated; so, an investigation about color enhancement is now on the make.

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