Computationally efficient algorithm for fuzzy rule-based enhancement on JPEG compressed color images

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Abstract: - In the past few years the resolution of images increased and the requirement for large storage space and fast process, directly in the compressed domain, becomes essential. Fuzzy rule-based contrast enhancement, is a well-known rather simple approach with good visual results. As any fuzzy algorithm, it is by default nonlinear, thus not straightforward applicable on the JPEG bitstream data – zig-zag ordered quantized DCT (Discrete Cosine Transform) coefficients. Because of their nonlinear nature the fuzzy techniques don't have yet a well-defined strategy for their implementation in the compressed domain. In this paper, we propose an implementation strategy suitable for single input – single output Takagi-Sugeno fuzzy systems with trapezoidal shaped input membership function, directly in the JPEG compressed domain. The fuzzy sets parameters are adaptively chosen by analyzing the histogram of the image data in the compressed domain, in order to optimally enhance the image contrast. The fuzzy rule-based algorithm requires some threshold comparisons, for which an adaptive implementation, taking into account the frequency content of each block in the compress domain JPEG image is proposed. This guarantees the minimal error implementation at minimum computational cost.

Key-Words: - Compressed domain processing, Discrete Cosine Transform (DCT), nonlinear operation, fuzzy rule-based contrast enhancement, fuzzy sets, color image enhancement.

1 Introduction

JPEG images had become an implicit standard for different kinds of environments, such as Internet or other applications where images of high resolution and reduced storage space are a must. Compressed domain image processing algorithms provide a powerful computational alternative to pixel level based implementations, especially considering the standards JPEG/MPEG. However, this field is in its beginning and the algorithms reported in the literature are mostly based on linear arithmetic operations between pixels. This linear approach is generally not suitable to implement contrast enhancement algorithms in the compressed domain, since most of them are by default based on nonlinear operations. Among the existing approaches such nonlinear image enhancement algorithms implementations on compressed domain image dates we mention the following [1-10]. Tang *et al.* [5] defined an algorithm based on the contrast, measured as the ratio of high-frequency content and low-frequency content in the bands of the DCT matrix. Kebin An *et al.* [6] uses the Tang algorithm but each block is enhanced according to its block classification: smooth block or high activity block. Kim *et al.* [7] developed a MPEG based image enhancement algorithm for people with low-vision, the contrast enhancement being performed by modifying the quantization matrices for inter and intra frames. Lee *et al.* [8] uses a basic concept of the Retinex theory for the enhancement of images.

A class of contrast enhancement methods is the ones based on fuzzy sets mathematics or fuzzy rule-based systems [11 – 13]. Fuzzy techniques offer a suitable framework for the development of new image processing methods because they are nonlinear and knowledge-based. They can process imperfect data if this imperfection originates from vagueness and ambiguity rather than randomness. Few of these frequently used fuzzy contrast enhancement methods have presented equivalent implementation in the compressed domain, probably because of their nonlinear nature.

We proposed in [3] another implementation in the compressed domain of an efficient contrast enhancement algorithm, based on the fuzzy INT operator. Here, as another alternative, we propose a fuzzy rule – based algorithm for contrast enhancement [3], approach applied on the RLE, zig-zag ordered quantized DCT coefficients, for JPEG images (available directly in the JPEG bitstream [1, 2]). The proposed approach can automatically determine the enhancement parameters, the thresholds involved, based on the DC histogram in the compressed domain of the image. The algorithm is applied only on the luminance component. However, it can be used to enhance color images as well, with no change of the chrominance components (which is a rather common approach in color image enhancement).

2 Algorithm description

2.1 Pixel level description of the fuzzy rule-based contrast enhancement algorithm

Image enhancement involves processing an image in order to make it visually more pleasant to the observers. It is one of the fundamental tasks in image processing; images have sometimes poor contrast or are blurred. Image enhancement includes a series of different point and spatial operations to improve the contrast, as: piecewise linear grey scale stretching transformation, grey scale clipping, histogram modification/equalization or even highly nonlinear grey scale mappings [14, 15]. Other classes of contrast enhancement methods are the ones based on fuzzy rules based systems [11-13].

Grey scale transformations, with the image contrast enhancement as a main application, are among the most frequent areas in which fuzzy techniques for image processing are applied [11, 12].

A possible way to express the image contrast enhancement in terms of fuzzy logic is by the means of a Takagi-Sugeno fuzzy rule based system [11, 13]. A common formulation assumes the description of the grey scale of the input image by 3 linguistic terms, denoted by *Dark*, *Gray* and *Bright.* Typically, the terms *Dark* and *Bright* are represented by trapezoidal-shaped fuzzy membership functions, whereas the term *Gray* is described by a triangular-shaped fuzzy membership function, as illustrated in Fig.1.a. Accordingly, on the universe of discourse of the output variable (i.e., the grey scale of the enhanced image), the other 3 linguistic terms are defined, referred heare as: *Darker*, *Midgray* and *Brighter*. Since we consider a Takagi-Sugeno fuzzy singleton (or, numerical constants denoted by l_v^d for *Darker*, l_v^g for *Midgray* and l_v^b for *Brighter*), as shown in Fig1.b. If one denotes the input variable (describing grey levels in the input range) by l_u, $l_u \in \{0, 1, ..., 255\}$, and the output variable (describing the gray level in the output image) by l_v, $l_v \in \{0, 1, ..., 255\}$, the fuzzy rule base of the Takagi-Sugeno contrast enhancement fuzzy systems comprises the following 3 rules:

R1: IF l_u is *Dark* THEN l_v is *Darker*
R2: IF l_u is *Gray* THEN l_v is *Midgray*
R3: IF l_u is *Bright* THEN l_v is *Brigter*,

or, equivalently,

R1: IF l_u is *Dark* THEN $l_v = l_v^d$ is *Darker*
R2: IF l_u is *Gray* THEN $l_v = l_v^g$ is *Midgray*
R3: IF l_u is *Bright* THEN $l_v = l_v^b$ is *Brigter*.

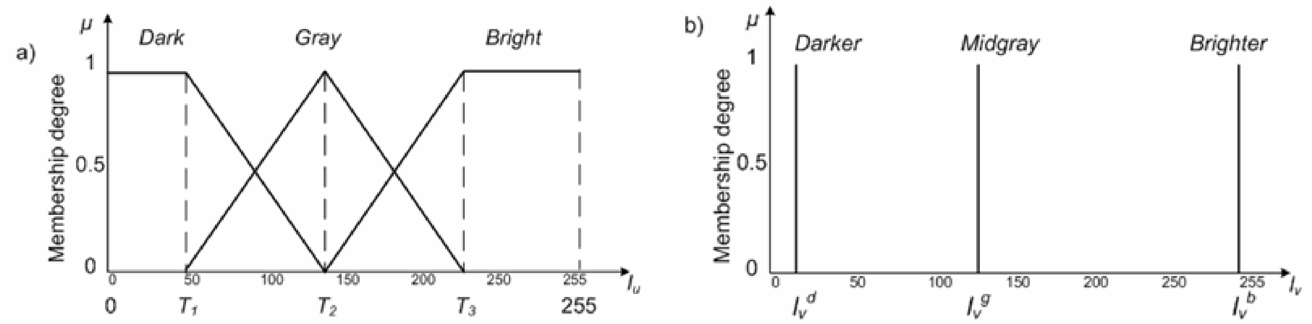

Fig.1. a) Input, and b) Output membership functions for fuzzy, rule-based contrast enhancement.

Then for any value l_u^* at the input of our Takagi-Sageno contrast enhancement fuzzy system, in the output image, the corresponding brightness l_v^* is obtained by applying the Takagi-Sugeno fuzzy inference, as:

$$l_v^* = \frac{\mu_{Dark}(l_u^*) \cdot l_v^d + \mu_{Gray}(l_u^*) \cdot l_v^g + \mu_{Bright}(l_u^*) \cdot l_v^b}{\mu_{Dark}(l_u^*) + \mu_{Gray}(l_u^*) + \mu_{Bright}(l_u^*)}, \quad (1)$$

where: $\mu_{Dark}(l_u^*)$, $\mu_{Gray}(l_u^*)$, $\mu_{Bright}(l_u^*)$ denote the membership degrees of the currently processed brightness l_u^* to the input fuzzy sets *Dark, Gray* and *Bright.*

In the implementation presented here, we assume that the input fuzzy sets form a fuzzy partition of the universe of discourse of l_u:

$$\mu_{Dark}(l_u) + \mu_{Gray}(l_u) + \mu_{Bright}(l_u) = 1 \quad (2)$$

The numerical constants defining output singletons were selected here at: $l_v^d = 1$ (black), $l_v^g = 127$ (gray), $l_v^b = 255$ (white).

For a general computational framework of any of the 3 membership degrees required by equation (1), we propose to represent each of the input fuzzy sets membership functions by a trapezoidal function $f_{tr} : L \to [0;1]$, where L is the dynamic grey level range of the image, $L = \{0, 1, \dots, 255\}$, represented generically in Fig.2, in analytical form:

$$f_{tr}(a,b,c,d,l_u) = \begin{cases} 0, & if\ l_u \in [0,a) \\ \dfrac{l_u - a}{b - a}, & if\ l_u \in [a,b) \\ 1, & if\ l_u \in [b,c] \\ \dfrac{-l_u + d}{d - c}, & if\ l_u \in (c,d] \\ 0, & if\ l_u \in (d,255] \end{cases} . \quad (3)$$

With this generic function f_{tr}, any of the 3 membership functions, $\mu_s : L \to [0;1]$, where $s \in \{Dark, Gray, Bright\}$, in Fig1.a can be expressed, for particular choices of the parameters *a, b, c, d*:

$$\begin{aligned} \mu_{Dark}(l_u) &= f_{tr}(0,\ 0, T_1, T_2, l_u) \\ \mu_{Gray}(l_u) &= f_{tr}(T_1, T_2, T_2, T_3, l_u) \\ \mu_{Bright}(l_u) &= f_{tr}(T_2, T_3, 255, 255, l_u). \end{aligned} \quad (4)$$

The thresholds: T_1, T_2 and T_3 are chosen from the image histogram like the minimum the mean and the maximum gray level values (as suggested in [11] and exemplified in Fig.5.a).

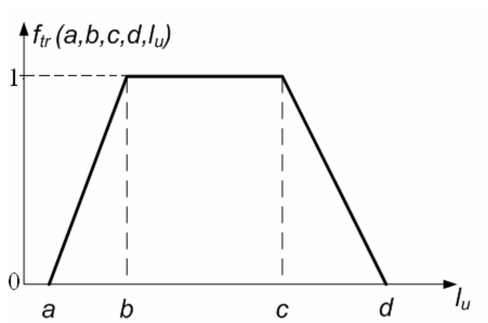

Fig.2. Function for computing the membership degree on dark, gray and bright.

2.2 The contrast enhancement algorithm reformulation in the compressed domain

If we have a JPEG compressed image is more efficiently to process it without performing decompression, pixel level processing, and recompression.

For linear operation we can use the DCT coefficients for processing the images, instead of pixels, the translation being straightforward. For nonlinear operations the translation of pixel level algorithms to the compressed domain (using the DCT coefficients available direct in the JPEG bitstream) is not directly, but once reformulated the algorithm is faster, and the decompression is avoided.

In the JPEG compression algorithm [1, 2], the image is first divided into 8×8 blocks, and each 8×8 block is individually processed. Considering the original $H \times W$ image, we denote any such 8×8 block of pixels by the matrix $U[8 \times 8]$, containing the grey level values of the pixels. On each block a DCT is applied providing the DCT coefficients which are quantized. Many small coefficients, usually high frequency ones, are quantized to zero. The next step is zig-zag scanning of the DCT matrix, followed by Run Length Encoding (RLE), and entropy coding (Huffman coding). In the decoder, the compressed image is decoded and then dequantized and inverse-DCT-transformed.

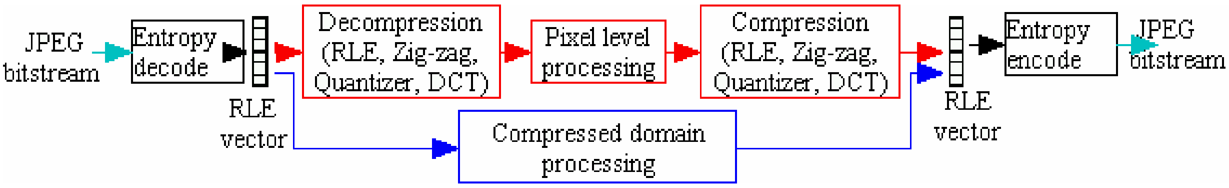

Fig.3. The two ways to process the image compressed JPEG

There are two ways to enhance the images which are compressed using JPEG (Fig. 3):

- The compressed domain processing - no decompression/ compression, but the enhancement algorithm must be formulated in the DCT image representation space;
- The pixel level processing – enhancement of the image after decompression, direct manipulation of the pixels is adopted, than recompress the enhanced image.

Processing in the JPEG compressed domain is made over the RLE vectors of the luminance only, with no change of the RLE vectors from the chrominance.
Every RLE vector contains data about the distribution of luminance (DCT coefficients) in an 8×8 pixels block of the image, following the rule beneath. We denote the RLE values by the line vector $U_{RLE}[1 \times 2N]$.

$$U_{RLE} = \{u_{RLE}[i], \quad i = 0, 1, ..., 2N\}. \tag{5}$$

where:

- $2N$ - is the length of the RLE vector ($2N < 128$).
- $u_{RLE}[0]$ - represents the value of the DC coefficient of the 8×8 block.
- $u_{RLE}[2 \cdot k]$ - represents the value of an AC coefficient ($k = 1, 2..., N$), and
- $u_{RLE}[2 \cdot k - 1]$ - represents the number of zeroes that precede the AC coefficient.

To obtain in the compressed domain the same processing results as the one given by the pixel-level approach presented in Section 2.1, the algorithm given in the previous section must be reformulated as a block level processing. The nonlinear operations, like the thresholding in fuzzy rule-based contrast enhancement algorithm, must be carefully addressed.
For 8x8 pixels blocks, instead of 64 data implied in the pixel level processing, in the compressed domain only a smaller amount of data is processed, because the majority of the coefficients in the DCT domain are zero after the quantization.

The DC coefficient gives the average brightness in the block and is used in our implementation as an estimate for selecting the processing rule for all the pixels in the blocks with small AC energy.
In our algorithm an adaptive minimal decompression is used: full decompression is no longer needed, but decompression is used for the block having many details, for an improved accuracy of processing.

2.2.1 The thresholds selection using the DC histogram in the compressed domain

As mentioned above, a reasonable choice for the thresholds values T_1, T_2 and T_3 (Fig.1.a.) would be the minimum, the mean and the maximum grey level from the image histogram. But, in the compressed domain image representation, the pixel grey levels are not directly available (without decompression). What we do have available are the average values of the grey levels in each 8×8 pixels block in the image, given by the DC coefficients of the blocks composing the image. Roughly speaking, if they would be the only ones used to reconstruct the pixel level representation (without any AC information), they would give an approximation of the image, with some block boundary effects/ distortions and some loss of details, but however still preserving the significant visual information. Therefore, the histogram built only from the DC coefficients (Fig.4.a) will have also approximately the same shape as the grey level histogram, built from pixel-level data (Fig.4.b).

2.2.2 The reformulation of the fuzzy rule-based algorithm in the compressed domain

In the JPEG compression steps, prior to applying the DCT on each block, all the luminance values are scaled symmetrically towards 0, from the [0; 255] range to the [-128; 127] range. Since we have in the compressed domain all the gray values scaled symmetrically towards 0, we should express all the terms in equation (3) in terms of these translated grey levels. Note that the resulting DC coefficient will also be scaled towards 0.

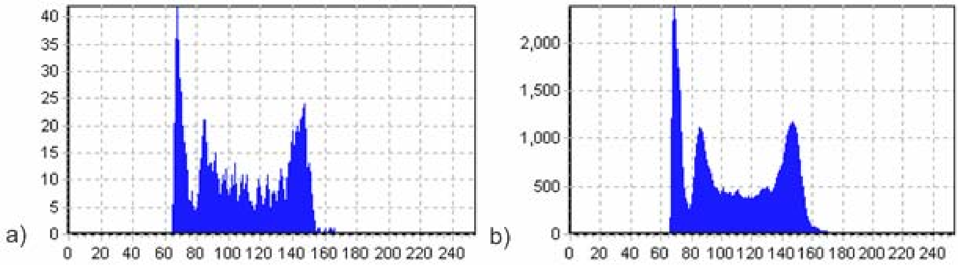

Fig.4. Histogram of *frog.jpg*: a) of DC coefficients in the compressed domain, b) at pixel level.

We will denote the translated version of a grey level l_u (with the original range [0; 255]) by l_u^t: $l_u^t = l_u - 128 \Rightarrow l_u = l_u^t + 128$.

To compute the membership degrees, we need to perform the operation of adding a constant and multiplying with a constant each pixel brightness value in a DCT block. These imply linear operations. The multiplication with a constant implies multiplying the constant with each coefficient from the DCT matrix, whereas the addition of a constant can be seen as a translation of the average brightness of the block, therefore it will affect only the DC coefficient of the 8×8 pixels block. These two scalar operations needed on the JPEG compressed image [1, 2], can be performed directly on the RLE vectors by simply changing the values - there is no need to reconstruct the quantized array or even the zig-zag vector.

Such an implementation avoids directly the multiplications where we have zero in the DCT matrix, since in the RLE vectors already the last strings of zeros are truncated. For these reasons, the operation is very fast.

Let $K_s[1\times 2]$ ($s \in \{Dark, Gray, Bright\}$) be the line vector of two constants (necessary for adding and multiplying the RLE vector) needed to compute the membership degrees in the compressed domain using the trapezoidal function:

$$K_s = [k_1^s, k_2^s] = f_{tr}^{DCT}(a,b,c,d,u_{RLE}[0]) = \begin{cases} [0 \quad 0], & if \quad u_{RLE}[0] \in [-128, a-128) \\ \left[\dfrac{1}{b-a} \quad \dfrac{128-a}{b-a}\right], & if \quad u_{RLE}[0] \in [a-128, b-128) \\ [1 \quad 1], & if \quad u_{RLE}[0] \in [b-128, c-128) \\ \left[\dfrac{-1}{d-c} \quad \dfrac{-128+d}{d-c}\right], & if \quad u_{RLE}[0] \in [c-128, d-128) \\ [0 \quad 0], & if \quad u_{RLE}[0] \in [d-128, 128) \end{cases} \quad (6)$$

Therefore, we will have:

$$K_{Dark} = [k_1^{Dark}, k_2^{Dark}] = f_{tr}^{DCT}(0, 0, T_1, T_2, u_{RLE}[0]) \quad (7)$$
$$K_{Gray} = [k_1^{Gray}, k_2^{Gray}] = f_{tr}^{DCT}(T_1, T_2, T_2, T_3, u_{RLE}[0])$$
$$K_{Bright} = [k_1^{Bright}, k_2^{Bright}] = f_{tr}^{DCT}(T_2, T_3, 255, 255, u_{RLE}[0])$$

Notice that: $u_{RLE}[0]$ is the corresponding DC coefficient of the 8×8 pixels block of the matrix U.

For each of the 8×8 pixels blocks the comparison with the thresholds in the compressed domain is done on the DC coefficient only, since generally it is reasonable to assume that a block level classification is likely to correctly place all the pixels in the block on the correct subrange of the membership function (where it is piece wise linear). This is valid for the blocks with moderate frequency content.

Once we have established in this fashion, for a certain pixels block, which of the 5 cases given by equation (6) seems more suitable to apply for all grey levels in the block, we directly compute the 3 vectors K_s ($s \in \{Dark, Gray, Bright\}$), which will be used to compute the 3 membership degrees of each pixel in the block to the fuzzy sets *Dark, Gray* and *Bright* in a single step for the entire block, using a matrix-vector formulation.

If one denotes by $M^s[8\times 8]$, $\forall s \in \{Dark, Gray, Bright\}$, the matrices of membership degrees of the 64 grey levels in the 8×8 pixels block to the 3 input fuzzy sets, then any element in M^s is given by:

$$M^s[i,j] = \mu_s(u[i,j]), \forall i,j = 0,1,...,7. \quad (8)$$

Furthermore, for all the elements in the block, the function μ_s is assumed to have the same linear form, generally speaking, $\mu_s(u[i,j]) = c_m \cdot u[i,j] + c_a$, with: c_m, c_a scalar constants for the multiplication and addition. So,

$$M^s[i,j] = c_m \cdot u[i,j] + c_a, \forall i,j = 0,1,...,7. \quad (9)$$

where: $C_a[8\times 8], c_a[i,j]=c_a, \forall\ i,j=0,1,...,7.$

Applying a DCT, quantization, zig-zag scanning and RLE on both sides of the equation (9), and denoting the resulting RLE vector obtained from M^s by $M^s_{RLE}[1\times 2N]$, one gets its form as:

$$M^s_{RLE}=c_m\cdot U_{RLE}+C_a^{RLE}\ , \tag{10}$$

where using the notations in equation (6):

- $C_a^{RLE}[1\times 2N], C_a^{RLE}=[k_2^s\ \ 0\ \ 0\ \ ...\ \ 0]$, and
- $c_m=k_1^s$, computed previously.

The fuzzy rule-based contrast enhancement algorithm, from equation (1) taking in account the equation (2), reformulated in the compressed domain as a block level processing, can be described by the following formula (we denote the RLE vector for the 8×8 enhanced block from the image with the $IntU_{RLE}[1\times 128]$):

$$IntU_{RLE}=M^{Dark}_{RLE}\cdot(l_v^d-128)+M^{Gray}_{RLE}\cdot(l_v^g-128)+ \\ +M^{Bright}_{RLE}\cdot(l_v^b-128). \tag{11}$$

2.3 The proposed adaptive algorithm for contrast enhancement

The comparison with the thresholds T_1, T_2 and T_3 would necessarily need the decompression; otherwise one cannot have the grey level value in each of the 64 possible spatial locations, but then we would return to what we aimed to avoid: full decompression before processing. The comparison with the thresholds is a nonlinear operation. Fortunately, let us recall that there are typically many 8×8 pixels blocks in general purpose digital images where the local variation of the brightness is small around the DC coefficient of the block. Thus for every such block, it is reasonable to assume that if its average grey level falls in one interval of the thresholds, on the same interval will be all the individual brightnesses of the pixels in the block.

Based on the RLE vector, one can see that the frequency content of each 8×8 block from the image can be estimated, classifying the blocks into uniform blocks or blocks with significant variable luminance. We compute the AC energy content from the block, energy denoted by E_{AC} and described by the following formula:

$$E_{AC}=\frac{\sum_{k=1}^{N}u_{RLE}[2\cdot k]}{63} \tag{12}$$

If E_{AC} is very small the block is approximately uniform (of almost uniform luminance).

Non-uniform blocks (of significant variable luminance) can contain only a few details, but significant for the object (for example, horizontal, vertical and oblique edges) or, a large number of significant details for the object (like in the case of a "chess table" of 8×8 block). In this case the quantity of E_{AC} is high.

An adaptive minimal decompression is used: full decompression is no longer needed, but decompression is used for the block having significant details, for an improved accuracy of processing [3].

If the computed estimate of the brightness variation E_{AC} in the currently processed block of 8×8 pixels exceeds a certain threshold, denoted here as e_{thd}, the decision is made to decompress the pixels block and process the luminance values individually, using equation (1). Otherwise, the brightness variation within the block is small enough to allow the selection of the processing function based only on the position of $u_{RLE}[0]$ towards the thresholds and do the processing in the compressed domain directly on the U_{RLE} vector, as described above, using the previously derived equation (11).

We chose from the experiments the e_{thd} value taking into account the image statistics with respect to the amount and magnitude of image edges (the amount and sharpness of the details within the image). Thus, for images with similar statistics with respect to the frequency content, the same AC energy threshold e_{thd} may be reliably used in the selection of the processing type (with/without decompression).

The proposed algorithm using fuzzy rule-base Takagi-Sugeno contrast enhancement is defined for each 8×8 pixels block of the JPEG image, as follows:

1. Compute the average of AC coefficients energy from DCT block, denoted E_{AC}, using equation (12).
2. If $E_{AC}<e_{thd}$ (uniform blocks) => process the block in the compressed domain using equation (11).
3. If $E_{AC}\geq e_{thd}$ (the block has a significant content of details) => decompress the block and process every pixel from the block separately, using equation (1).

3 Experimental results

The algorithm was tested on different images having different statistics, with different contrast factors and different average luminance, collected from different sources. The experimental results show a much better computational efficiency, compared to the standard processing method, which needs a total decompression of the image.

Results of enhanced images using the proposed algorithm are presented in figures 6, 7, 8, 9, 10,11 below. In Fig.6. we have the original image *frog.jpg* with the histogram from Fig.5.a and the enhanced image with the histogram in Fig.5.b.

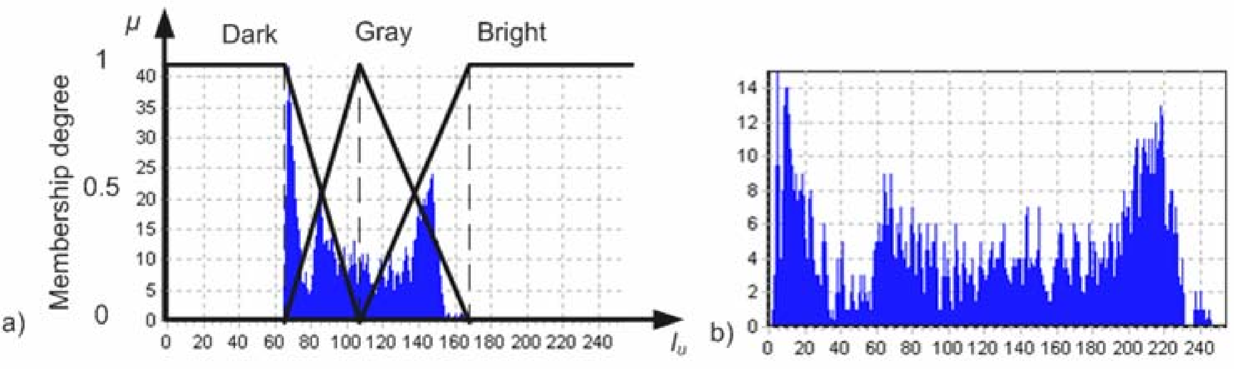

Fig.5. a) Input membership function superimposed on the DC histogram of *frog.jpg*;
b) DC histogram of *frog.jpg* after fuzzy contrast enhancement.

Fig.6. Original and enhanced image *frog.jpg*

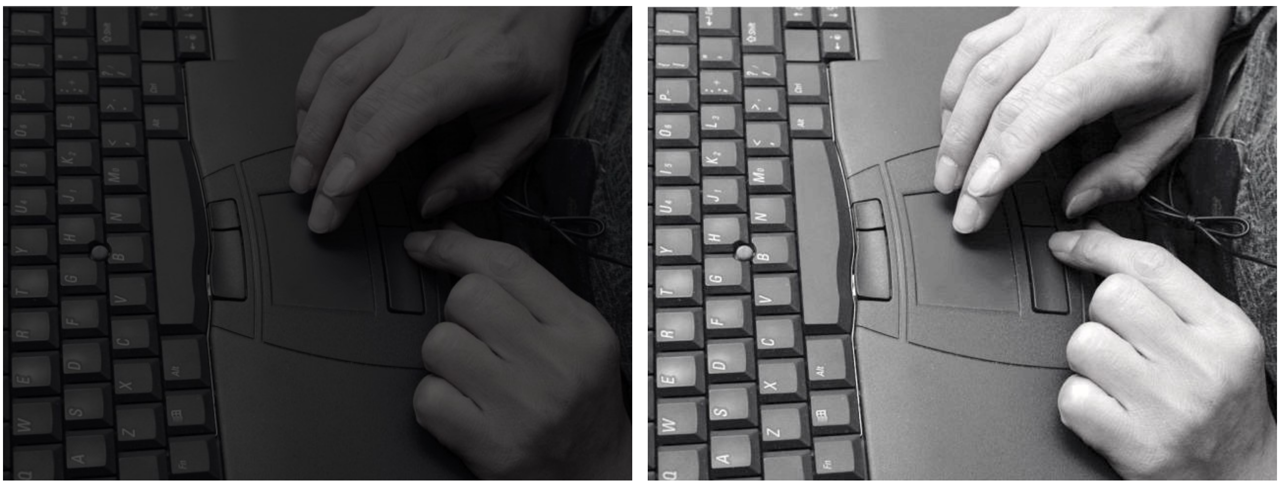

Fig.7. Original and enhanced image *keyboard.jpg*

Fig.8. Original and enhanced image *woman.jpg*

Fig.9. Original and enhanced image *Lena.jpg*

Fig.10. Original and enhanced image *Cars.jpg*

Fig.11. Original and enhanced image *Monarch.jpg*

The MSE (Mean Squared Error) between the pixel level processed images and the images processed with our algorithm was used as quality performance measure. The efficiency (*EffBlocks*) of the proposed method formulated above for the compressed domain, is evaluated by examining the number of blocks processed at pixel level as percent from the total number of 8×8 pixels blocks in the image.

Table 1. Results for different values e_{thd}

Image	$\mathbf{e_{thd}}$	T_1	T_2	T_3	**EffBlocks [%]**	**MSE**
frog.jpg	5	66	104	166	20.2	1.9
woman.jpg	5	78	141	191	15	0.44
Lena.jpg	5	33	126	223	20.1	0.004
Lena.jpg	10	33	126	223	15.03	0.005
Lena.jpg	20	33	126	223	10.41	0.02
keyboard.jpg	10	0	34	78	16.02	0.01
eye.jpg	10	3	117	199	14.6	1.78
medical.jpg	10	5	90	208	10.07	0.93
butterfly.jpg	10	32	117	207	10.58	0.011
cars.jpg	5	106	161	200	8.16	0.5
bee.jpg	10	7	170	48	15.4	0.55
fingerPrint.jpg	10	45	117	190	18	0.29
children.jpg	10	60	128	228	13.1	0.28
monarch.jpg	10	29	101	223	16.15	0.63
lisa.jpg	10	33	88	223	14.9	1.5
girl.jpg	10	76	104	174	7.24	2.1

A very small e_{thd} value will always lead to images of a very good quality, but the number of processed blocks in the compressed domain will be quite small, so the complexity of the computing algorithm is not significantly smaller, compared to the direct processing on the pixel. An appropriate e_{thd} value will lead to the increase of the number of blocks processed in the compressed domain and, in this way, a fast fuzzy algorithm for image enhancement could be obtained.

The proposed approach can automatically determine the enhancement parameters, the thresholds involved, based on the DC histogram in the compressed domain of the JPEG image data.

4 Conclusion

A new algorithm for the compressed domain implementation of fuzzy rule-based contrast enhancement has been proposed and verified through several experiments on gray scale and color images. The selection of the fuzzy sets membership functions parameters was done directly in the compressed domain, using the histogram of the DC coefficients of the compressed blocks as an approximation of the grey level statistics of the image. The algorithm was tested on different images having different statistics, with different contrast factors and different average luminance's.

The proposed algorithm is fast, allowing to save memory and significant computational time, compared to the standard processing method (which needs a total decompression of the image), practically at no processing error as compared to the pixel level algorithm.

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