Comparative Analysis of Some Dynamic Range Reduction Methods for SAR Image Visualization

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Abstract. The main objective of the paper is to present our comparative investigations of high dynamic range compression to demonstrate the SAR images on monitors with the standard dynamic range. To display the images we need to compress the input image range in 256 times with preservation of the most object details and maximal image contrast. We studied several well-known tone mapping methods developed for optical images and used some published no-reference quality measures for evaluation of the obtained dynamic range compression results.

Keywords: SAR · HDR · Satellite imagery · Image processing

1 Introduction

Synthetic aperture radar (SAR) is a popular type of radars, which is used on satellites to create images of the Earth. SAR uses the motion of the radar antenna over a targeted region to provide finer spatial resolution than is possible with conventional beam-scanning radars. Modern satellite radar systems provide resolution of about 1 m in x-band with 2.4–3.75 cm wavelength. Signals of backscattered microwave pulses are reflected from the ground and storied in SAR images as pixels intensities. Pixel values are lower over flat ground. However, they increase in some cases due to backscattering from metal and stone objects. That is why the pixels have a high dynamic range of luminance levels: from 0 to 65535. SAR images belong to the class of High Dynamic Range (HDR) images.

The conventional method used to display SAR images on standard monitors contains a drawback: without compression of intensity with dynamic range, SAR images cannot be displayed with adequate contrast of all details. Standard or low dynamic range of monitors is [0–255] and may be abbreviated as SDR or LDR.

There is a very important problem to compress a HDR SAR image into an LDR-representation with minimal information lost and maximal contrast preservation. We denote this transformation as HDR-LDR transform.

The linear compression does not solve the problem of HDR-LDR transformation because from 80 to 90% of pixels have intensity values in the range [0–255], but large changes in pixel values occur around regions containing artificially made objects. That is why compression in 256 times produces mostly black image with some tiny gray or white blobs.

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In the literature, similar transformations are called tone mapping [1–3] and mainly are applied to images registered by optical systems. An ideal HDR-LDR transformation needs to be done with the minimum loss of information and correlate with the human visual system. All the tone mapping transformations may be divided into two types: global and local. Global means that a intensity transformation function depends on the intensity value of the processing pixel independently of other. Local one means that the transformation function depends on intensity values of a neighborhood of the processing pixel. As the result, transformations of the last type take more time.

We have formulated several requirements for a HDR-LDR transformation function *f*:

(I) Total ordering. Scene-to-monitor mapping must be monotonic, i.e. if there are two pixels with gray values $A_1 < A_2$, after a HDR-LDR transformation *f* brightness of the pixels should satisfy to the inequality $f(A_1) \leq f(A_2)$. This means that the functions *f* must be nondecreasing ones.

(II) Preservation maximum contrast. Higher contrast of the resulting image means better quality of the transformation result. If for two pixels with gray values A_1 and A_2, we have $contrast(A_1) < contrast(A_2)$, after the transformation it must be $contrast(f(A_1)) \leq contrast(f(A_2))$, where $contrast(Y)$ means contrast abound pixel Y. To measure quality of the result, we need a quality function. Compare image quality, in particular image contrast, after several transformations, we can select the better transformation for convenient visual evaluation of the result.

(III) Fast calculation. The transformation must be fast, because real SAR images in our experiments were up to 27083 × 43750 pixels and there are very few local transformation, which satisfy to this requirement.

In this study, we have limited our considerations by the most popular tone mapping transformations developed for optical images and evaluated their applicability to SAR images.

The other sections of the paper are organized as follow: in Sect. 2, we briefly discuss HDR-LDR transformations used in the study; in Sect. 3, we outline some quality measures used for the transformation comparison; in Sect. 4, the experimental results are presented.

2 HDR-LDR Transformations

Very few papers are devoted to HDR-LDR transformation of SAR images. In [1] the authors apply k-means image clustering into 6 classes, different intensity compression for every class, and some additional pre- and post-processing of the result. Unfortunately, the authors used only visual comparison of the studied methods.

In [2] several dynamic range reduction techniques known from the tone mapping of optical images were analyzed regarding their applicability to SAR data.

Nonlinear luminosity correction is a popular image processing method that was applied for TV-sets and monitors since the middle of the last century. J.R. Little in [4] have described mainly concave functions like logarithmic and exponential. In [5] it was shown similarity between the logarithmic type of image processing model and the

Naka–Rushton model used for description of the human visual system (HVS). Similar model was used by Reinhard et al. in [6].

We examined global tone mapping transformations developed for optical images but suitable for SAR imaging. All of them must be concave and may be divided into 2 groups:

– monotonically increasing nonlinear functions (like exponential, logarithmic, μ-law [7]),
– S-shaped functions (like sigmoid).

Following to recommendations of paper [2] we have selected the most popular HDR-LDR transformations that may be used for SAR image visualization. In the semi-logarithmic scale, the luminosity transformation functions studied in this paper looks as presented in Fig. 1. In the figure the following legend is used: Ashikhmin global and local means two variants developed in [8], Reinhard is the photographic tone mapping from [6], Reinhard-Devlin is the photoreceptor model from [9], Drago is the logarithmic mapping from [10] and mu-lawis described in [7]. We also tested direct logarithmic mapping, gamma-based mapping and Schlick uniform rational quantization mapping [11].

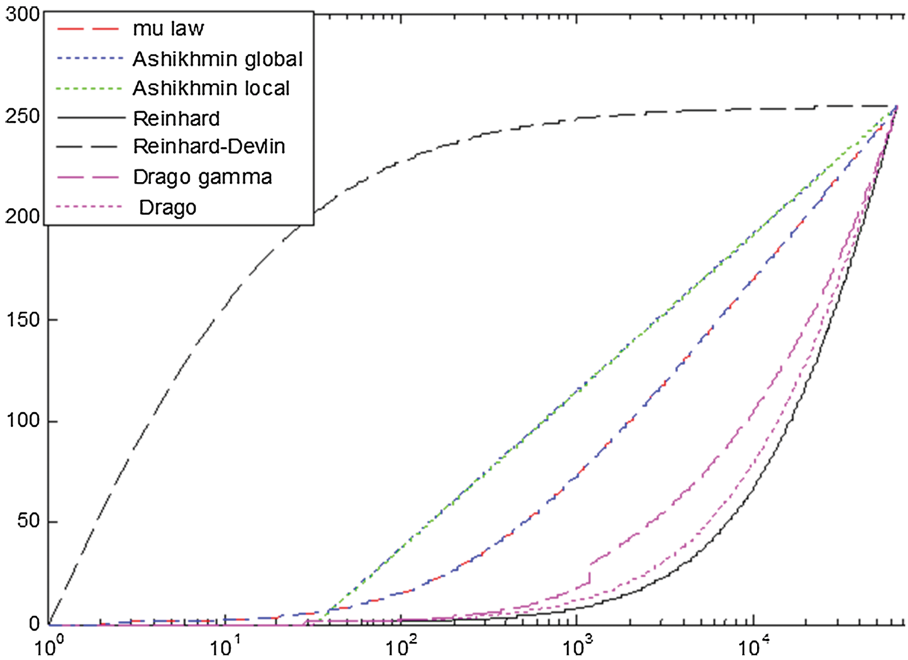


Fig. 1. Functions of several HDR-LDR transformations in the semi-logarithmic scale

Short descriptions of the mentioned measures are given below. In the following, the input data are amplitude values A. They are normalized to the range [0, 1], without normalization we denoted them as A_s. A_d means display luminance, $(L_d - 1)$ means display maximal gray value, $(L_s - 1)$ is the SAR image maximal gray value.

Direct logarithmic mapping may be described by the following function:

$$A_d = k^* \log(1 + cA_s) \big/ \log(1 + c), \tag{1}$$

where c – is a constant,
k – is a normalizing coefficient.
Gamma Mapping:

$$A_d = \left(L_d - 1\right)^* (A)^g, \tag{2}$$

the exponent value $g > 0$ and it is the main parameter of the function.
Drago Logarithmic Mapping [10]:

$$A_d = \left[m \,/\log(1 + c)\right]^* \; \left[\log(1 + cA)/\log\left(2 + 8A)^b\right)\right] \tag{3}$$

where c – is analogous to the simple logarithmic mapping,
m determines the brightness of the result,
b steers the amount of contrast.
Reinhard–Devlin Photoreceptor Model [9] is motivated by human eye photoreceptor behavior.

$$A_0 = lA + (1 - l)A_{\text{avg}},$$

$$A_d = A/[A + \left(lA_0\right)^p\big],$$

where the constant $l \in [0, 1]$, A_{avg} – the average amplitude value, $l \in [-8, 8]$, the constant p is computed from the minimum and average amplitude values with the exponent value 1.4:

$$p \;=\; 0.3 + 0.7((1 - A_{\text{avg}})/(1 - A_{\text{min}}))^{1.4}.$$

The parameter l steers the light adaptation term and influences the contrast in the resulting image. The parameter l determines the brightness.

In Figs. 2, 3, 4, 5, 6 and 7 below, we present some examples of high dynamic range compression for display of real SAR images. We demonstrate results of the presented HDR-LDR transformations on afragment of the big SAR image.

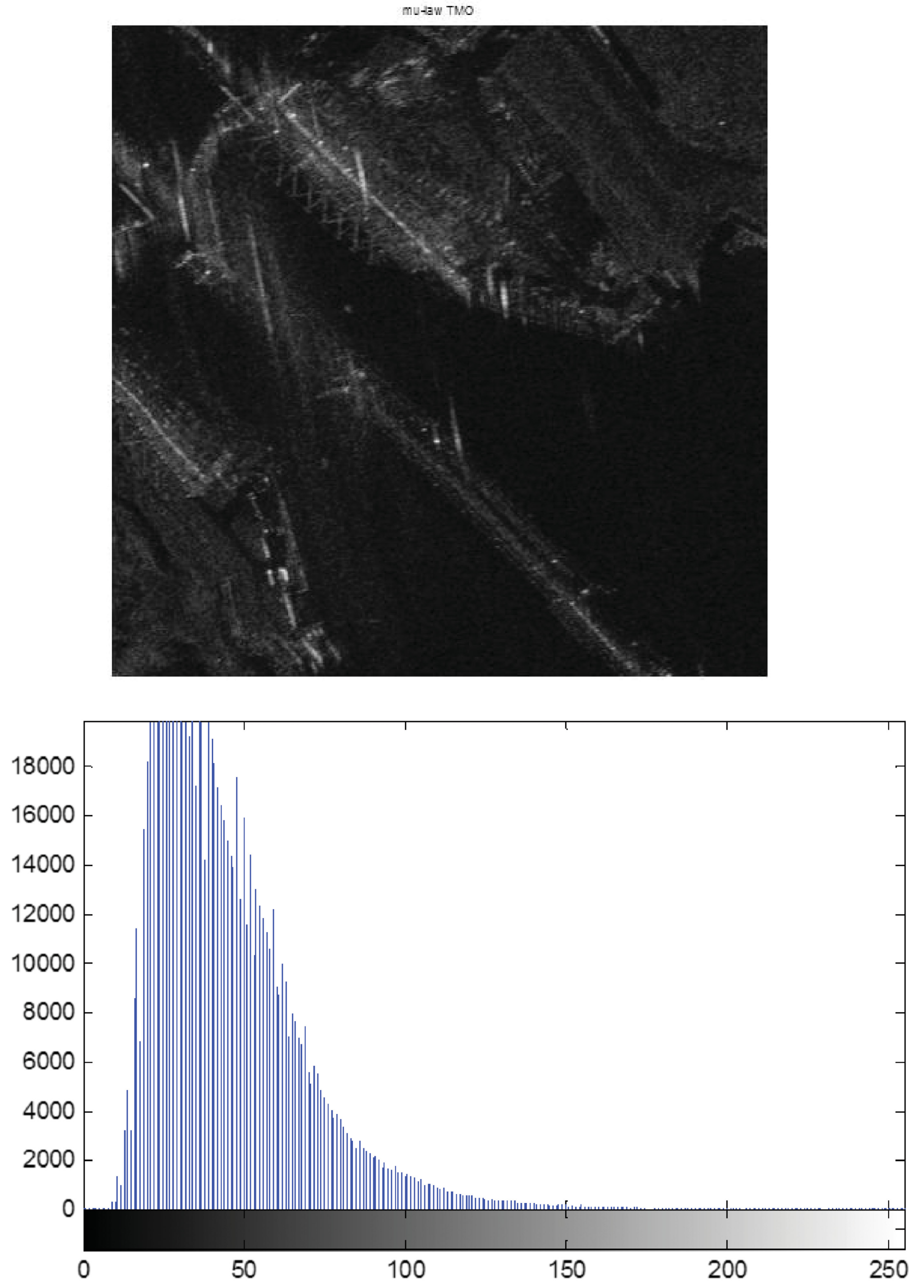
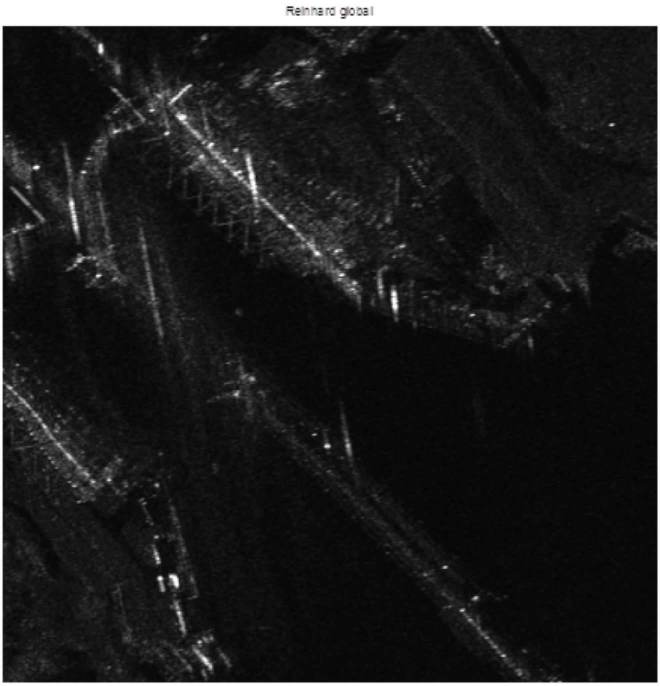


Fig. 2. A fragment of a SAR image compressed by mu-law transformation [7] and the image histogram



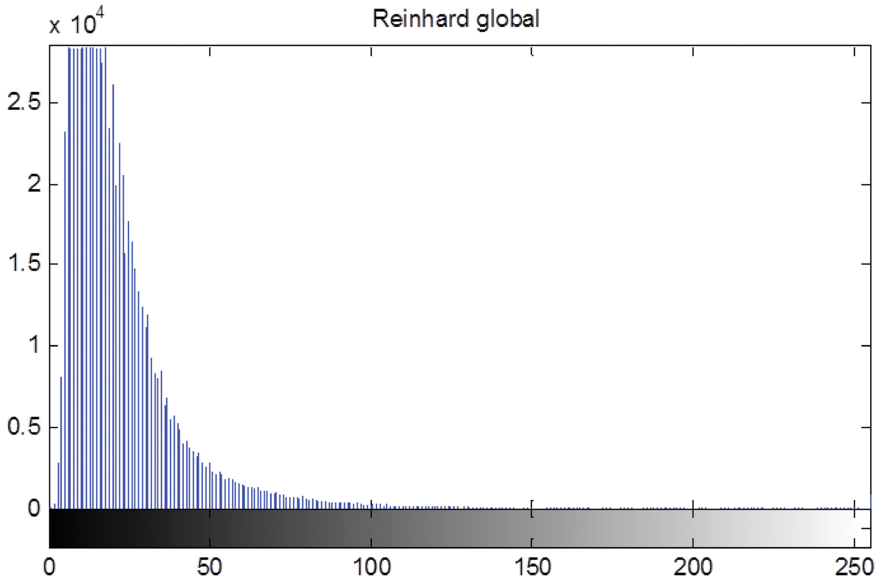
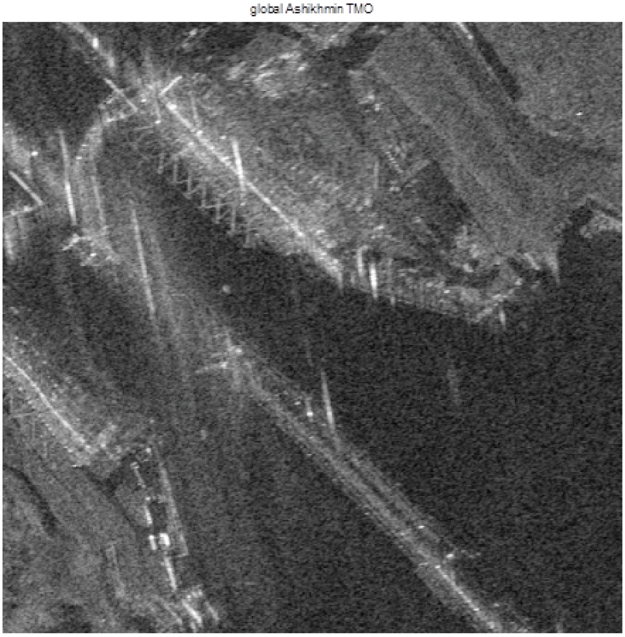


Fig. 3. The same fragment of a SAR image compressed by the Reinhard transformation [6] and the image histogram



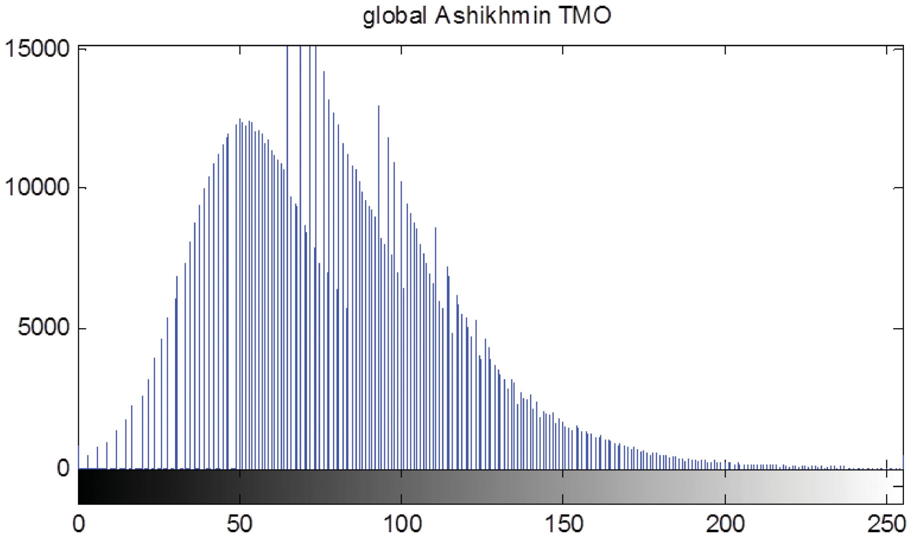
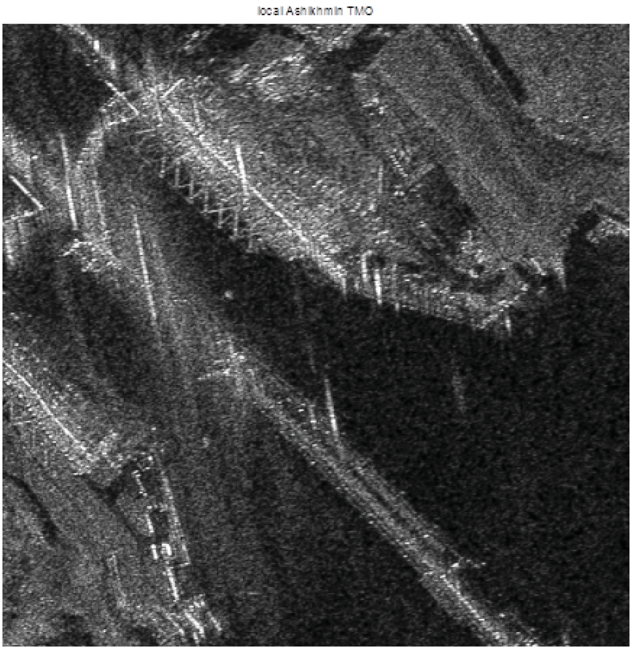


Fig. 4. The same fragment of a SAR image compressed by the global Ashikhmin transformation [8] and the image histogram



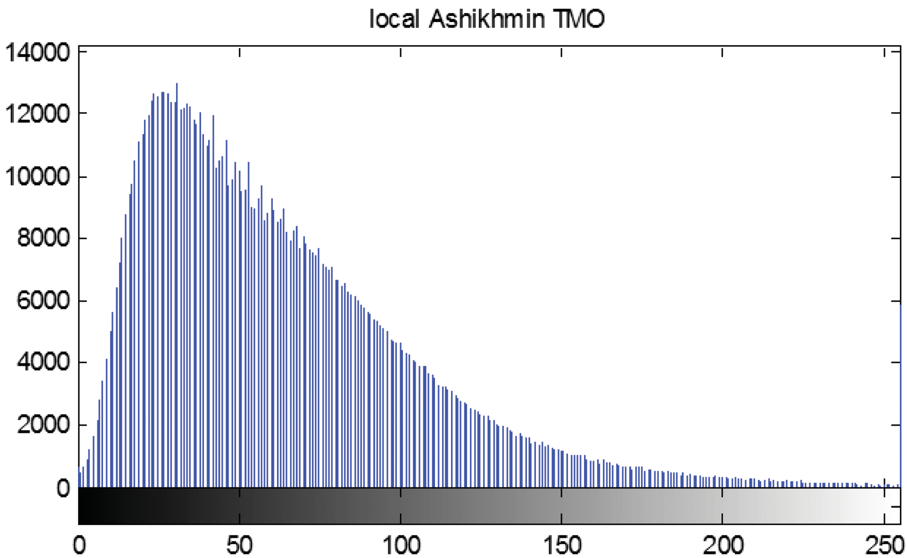


Fig. 5. The same fragment of a SAR image compressed by the local Ashikhmin transformation [8] and the image histogram

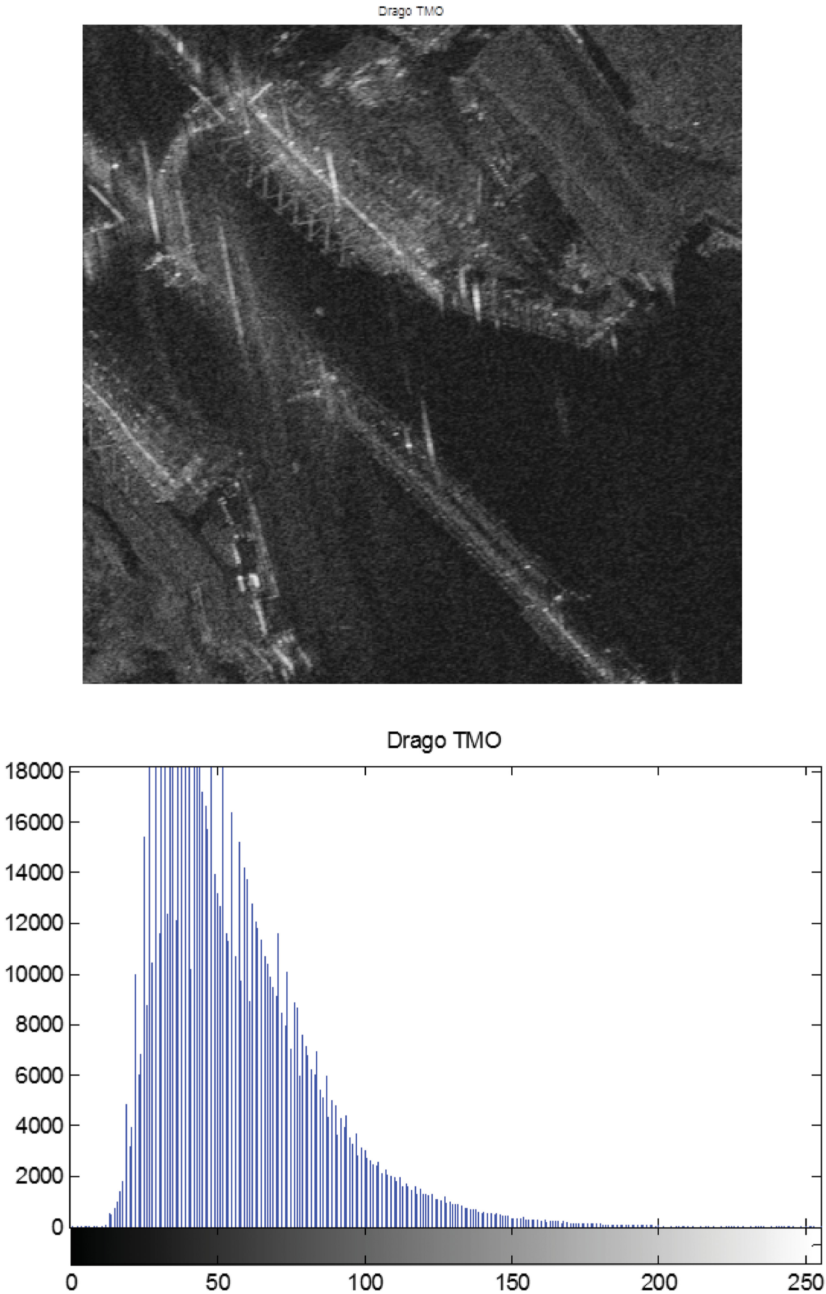
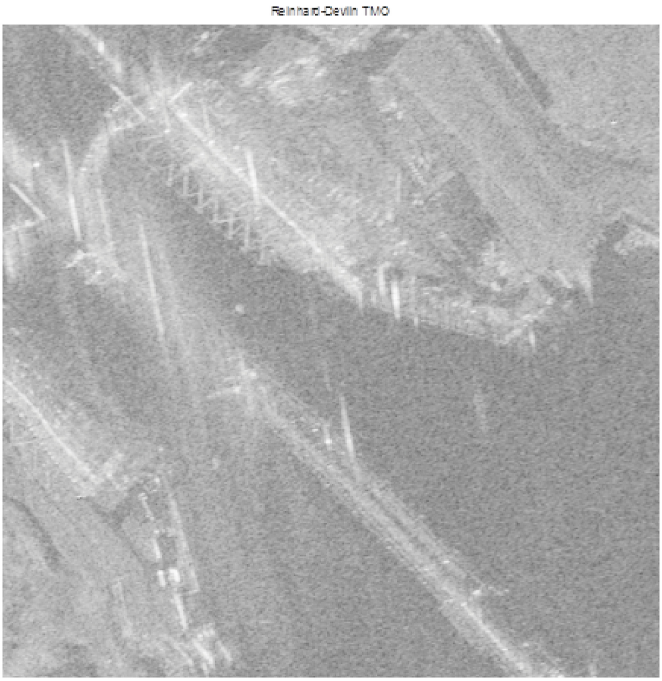


Fig. 6. The same fragment of a SAR image compressed by the Drago transformation [10] and the image histogram



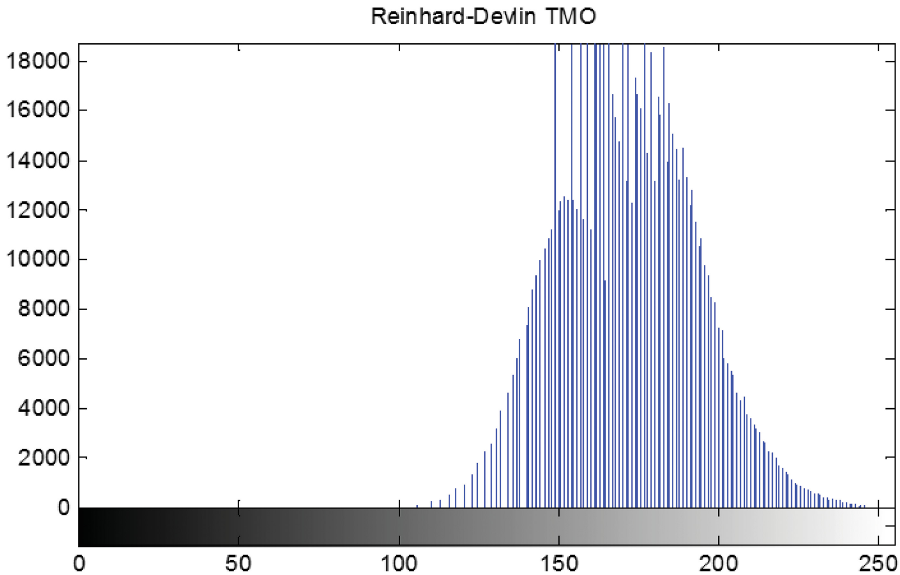


Fig. 7. The same fragment of a SAR image compressed by the Reinhard-Devlin transformation [9] and the image histogram

Visual quality evaluation of the presented figures gives us the following results. The background is usually dark, the metal and artificially created objects are very bright, speckle-noise and other kind of noise are also presented in the picture. The main objective of the tone mapping transformation is to get the best image contrast. Nevertheless, even for the six demonstrated pictures visually difficult to identify images with better contrast.

For several transformations mentioned in the previous section have infinite number of parameter variants. Because we reduce the original image, range in 256 times, two questions arises: (1) which transformation will produce better result, (2) which set of the transformation parameters will better present image contrast or sharpness. It is impossible to get answers using just visual evaluation of the results.

3 Quality Measures

To find answers one can use various image quality assessment (QA) measures. We do not have the ideal image for comparison with our transformed variant that is why we need in a so-called no-reference (NR) quality measure. Last decade no-reference measures were studied very actively, we just call a few major works such as [12–14].

The main features in our research are contrast, sharpness and naturalness of the image after dynamic range compression. The desirable NR-measure must be also highly correlated with the human-subjective evaluation of the image quality.

Among this class of measures, we have selected and studied TMQI metric [15] by Zhu and Milanfar, S3 measure of sharpness by Vu et al. [16], sharpness index by Blanchet and Moisan [17], sharpness metric by Leclaire and Moisan [18], BIQAA measure by Gabarda and Cristybal [19], the blur measure by Crete et al. [20]. We added to mentioned set of measures two sharpness measures calculated from gradients and image entropy. To save space, we will not describe these measures.

4 Experiments

We tested the mentioned tone mapping transformations and applied the mentioned NR image quality measures to the results obtained from real SAR images downloaded from the publicly available website [21].

We have formulated the following requirements to NR quality measure:

- the function should be fast,
- it smoothly changes the values when we smoothly change the HDR-LDR transformation parameters,
- it has one global extremum appropriate optimal set of the parameters,
- the extremal measure value correlate with the best human quality image estimation.

In Table 1 we have collected some estimates from our experiments. The top line of the table lists the tone-mapping methods. The bottom line gives the running time of every method. The middle lines demonstrate quality values of the used quality measures (they are listed in the first column). The most-right column presents the execution time for mapping transforms and the quality measure calculation respectively. MATLAB programs were used for image processing and running experiments. Some programs have been downloaded from the website of the authors of the mentioned articles and adapted, others were written by myself. They are not optimized and are used only for relative comparison.

Table 1. Tested tone mapping transformations and NR-quality measures

Method, measure	[7]	[6]	[9]	[10]	[10]	[11]	[8loc]	[8glob]	
Our blur measure	**0.170**	0.164	0.159	0.119	**0.170**	0.173	0.160	0.164	0.171
Entropy	6.282	6.299	6.331	2.259	6.547	7.127	**7.201**	6.977	**0.015**
ssim	0.481	0.380	0.402	0.001	0.615	0.001	**0.799**	0.746	0.265
Crete blur	**0.332**	0.329	0.304	0.235	0.330	**0.332**	0.309	0.316	0.218
JNBM, Karam	8.837	9.480	8.550	**14.995**	8.673	8.399	8.983	8.397	2.558
CPBD, Karam	**0.364**	0.328	0.297	0.277	0.297	0.269	0.266	0.278	1.872
TMQI	0.245	0.247	0.256	**0.702**	0.261	0.275	0.262	0.332	0.936
Naturalness	0.026	0.018	0.095	0.000	0.090	0.000	0.145	0.488	0.436
	0.125	0.359	0.359	0.156	0.390	0.171	1.653	0.249	Time, sec

Note: the best parameter values and methods are printed by bold.

Best values in Table 1 are highlighted in bold. From Table one can see that the fastest NR quality measure is entropy, followed by is our blur measure measure which is similar to the Crete measure. Both of them are used low-pass filtering of the initial image and calculate the maximal mean difference between vertical or horizontal variations of two image (input and the blurred one).

Shortly we can say that the Drago variant with gamma correction produce a very bright image, but the JNBM measure of Karam indicates that it is the best variant of tone mapping. The measure has the longest running time. So, it is not a good quality measure. Similar we can reject the TMQI measure developed by Zhu and Milanfar.

Then we tested simple exponential function changing gamma parameter and analyzing behavior of the quality functions. The sharpness index by Blanchet and Moisan increases monotonically and gives the biggest value for biggest gamma, but such DDR-LDR transformation produces almost binary image without any gray values. This means that this sharpness index is a bad measure and we rejected it.

μ-law [7] is the fastest variant of HDR-LDR transformation and there NR quality measures indicate that it is the best variant of tone mapping for SAR images. This evaluation correlate with our visual evaluation also, see Fig. 2.

5 Conclusion

The fastest tone mapping transformation is mu-law, followed by is local variant of Ashikhmin transformation (compare Fig. 2 with Fig. 5). Both of them correlate with the human quality estimation of the transformed images.

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