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The method of Compression of High-Dynamic-Range Infrared Images using image aggregation algorithms

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Abstract

In the article a method of compression of High Dynamic Range of Infrared images and its details enhancement was proposed. The method is based on aggregation of partial images with different ranges of pixel values generated on the basis of weighting function. Aggregation of images could be performed according to proposed scheme with use of the optimal algorithm selected by user. Preliminary results shown that the method can reveal previously hidden details in the original image.

1. Introduction

Nowadays, modern infrared cameras can detect temperatures and produce images that have a wide dynamic range of 14-bit (or more). Such dynamics exceeds sensitivity of human eye (7-bit) and typical 8-bit display devices. High dynamic range infrared images can be acquired during observation of different industrial installations and processes as well as in other situations e.g. in car night vision systems. From qualitative analysis point of view, displaying wide dynamic range infrared images on lower dynamic devices could hide the image details, forcing the user to change the range and level of the displayed image pixel values. Hence, compression methods which could reduce the data range must be applied in order to enhance the significant details of images and improve the image visual quality. Compression of high dynamic range infrared images also could be useful for automatic qualitative image processing procedures where use of images with lower range could reduce processing time. From quantitative analysis point of view compression of high dynamic range infrared images should take into account radiometric properties of camera in order to obtain proper temperature values. Dynamic-range compression (DRC) has been widely investigated and a number of visualization techniques have been proposed in literature [1][2][3][3]. One of the most popular technique for image compression and enhancing image contrast is an automatic gain control (AGC) and histogram equalization (HS). This technique tends to change the brightness of an image, increase the noise level lost in details and washed-out effect in some almost homogeneous area. To overcome these problems, some methods such as Plateau Histogram Equalization, Adaptive Histogram Equalization (AHE) or Range Limited Bi-Histogram Equalization (RLBHE) has been proposed. There are also advanced methods for visualizing high dynamic range infrared images. These methods applies the balanced Contrast-limited adaptive histogram equalization (CLAHE) and contrast enhancement (BCCE), bilateral filter and dynamic range partitioning (BF&DRP) or technique based on two-scale decomposition of the image into a base layer and a detail layer with use the bilateral filter. In this article a method of compression of high dynamic range infrared images based on weighted control of image range and image fusion methods is proposed and described.

2. Proposed method

The aim of the proposed method is to compress the high dynamic infrared image while enhancing the visibility of image details. Due to application of the method to qualitative image analysis purposes, it was assumed that method may not preserve information about temperature values. The method consist two main steps (Fig. 1.). First on the basis of single radiometric image (primary image) a set of auxiliary images (secondary images) with different ranges is generated (Fig. 1a). In the second step images are joined using appropriate image aggregation method (Fig 1b). As a result of fusion procedure compressed image (final image) with visible all details masked in primary image is obtained. Generation of secondary images involves gradual change of primary image range in two passes: from lower to higher values and from higher to lower values. Such procedure gives two sets of secondary images called respectively low (LSSI) and high (HSSI) set. Number of secondary images is defined by the user. Gradient of the range changes is defined by the weighting function which could be also selected by the user. Weighting function could be common for generation both low and high set of secondary images or user could assume different type of functions. Aggregation of the sets of secondary images could be performed according to scheme presented in Fig. 1b. Using proposed aggregation scheme a two partial aggregation images called LAI and HAI are generated. Those partial images could be used for further analysis. Final image LHAI is created on the basis of fusion of aggregated partial images.

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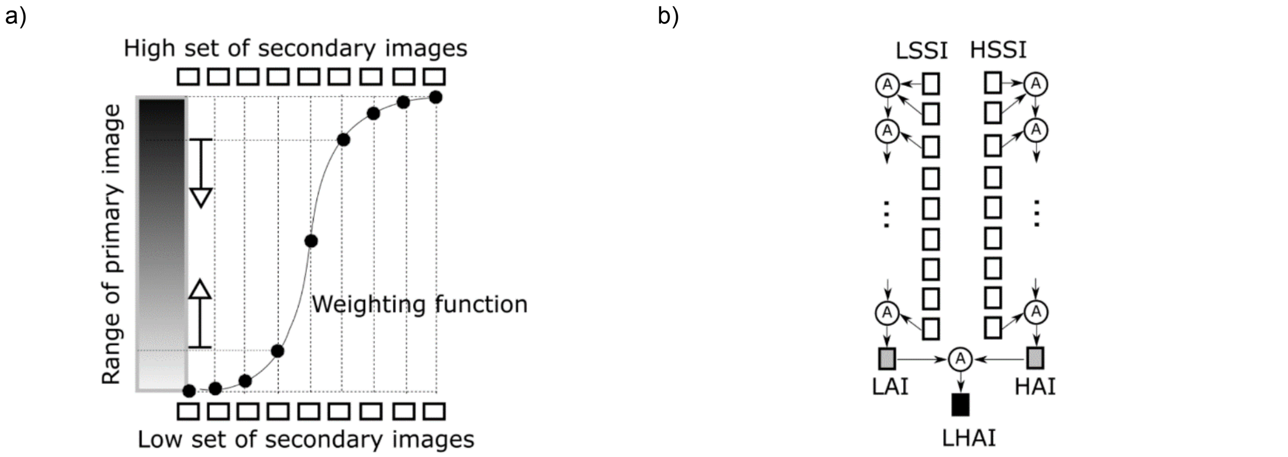


Fig. 1. *Illustration of the method: a) generation the sets of low and high auxiliary images, b) scheme of aggregation of auxiliary images*

3. Method verification

The proposed method was tested using infrared image (Fig.2a) recorded during inspection of industrial installation in a power plant. Image was recorded in radiometric format which allow calculation of temperature values of image pixels. The image resolution is 320x240px and showing a scene with industrial objects whose temperatures values were scattered in a wide range (135°C) what is also visible in Fig 2b where image histogram is presented. In the original image indicated areas where image details in not visible due to high dynamic range of image values.

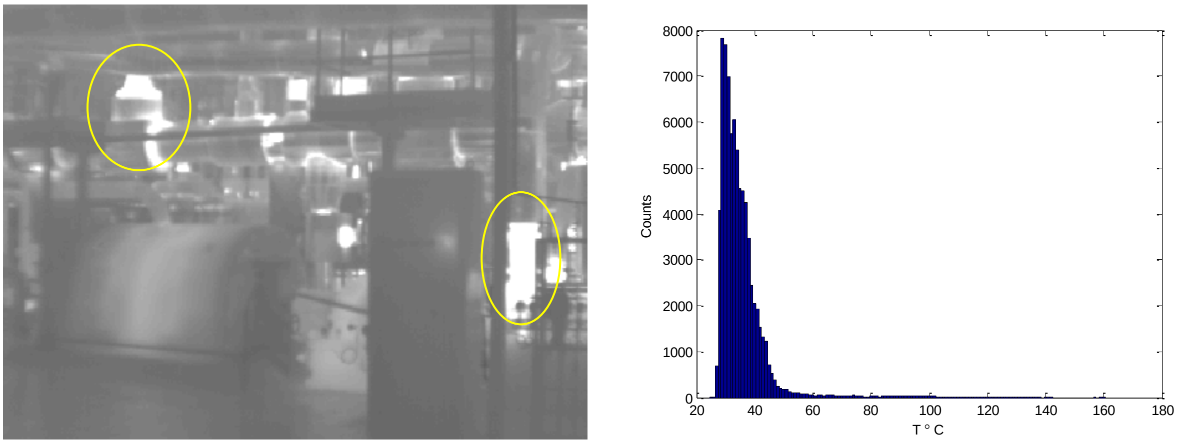


Fig. 2. *Original image (a) its histogram (b)*

According to proposed method it was assumed that weighting function could be a log-sigmoid transfer function defined in the following way:

$$y = \frac{1}{1+e^{-\beta x}} \tag{1}$$

The function values depend on β parameter which allows to weight image values in different way. During the research several functions for different β parameters ranged from 0.1 to 2 were generated. Exemplary functions were presented in Fig. 3.

For each function two secondary image sets consisted respectively 15 and 30 images were generated. Selected secondary images from low (LSSI) and high (HSSI) set were presented in Fig. 4. Finally for the research purposes a 40 sets of low and high secondary images were subjected to further operation like aggregation using two different image fusion algorithms.

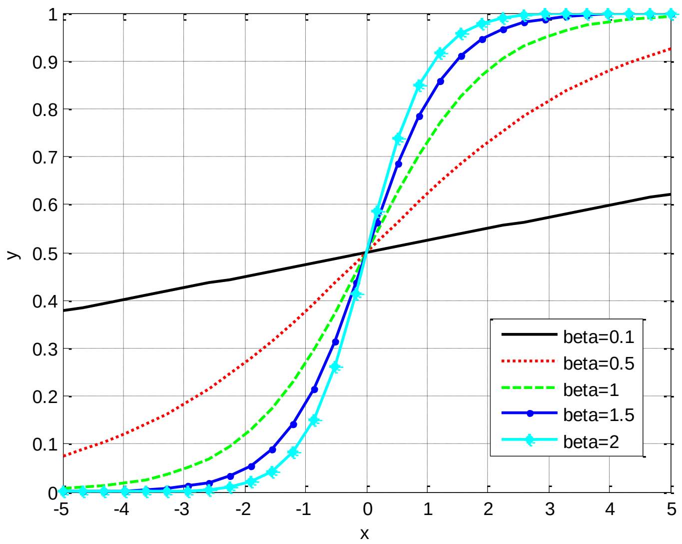


Fig. 3. *Selected weighting functions used during the research*

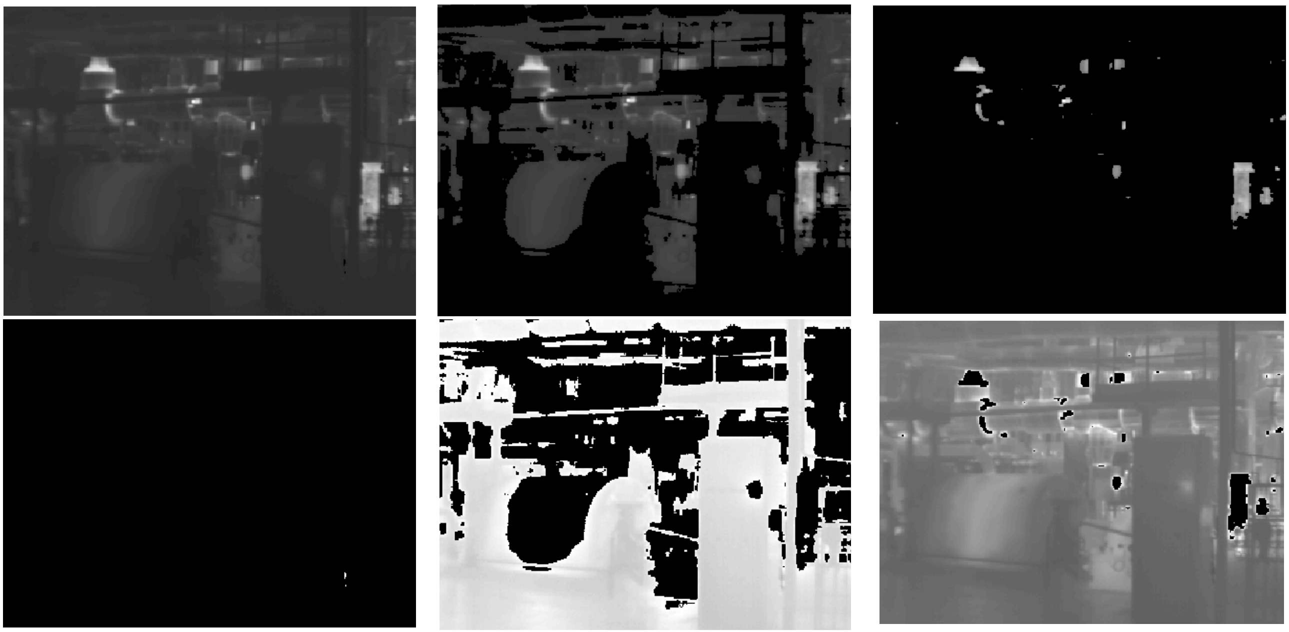


Fig. 4. *Exemplary secondary images from high (upper row) and low (lower row) set*

3.1. Fusion of partial images

Image fusion is a process of combining relevant features from input images of the same scene to form a single enhanced image. The main advantage of such approach is the preservation of important information content from input images, while redundant information is reduced. Image fusion can be performed in the spatial domain or in the transformation domain. Different fusion methods have been proposed in literature. In the spatial domain there are methods of various complexity. Starting from simple point operators, like pixel averaging to PCA analysis [7]. The disadvantage of spatial domain approaches is that they produce spectral distortion in the fused image, while the main advantage is low computational time. Multiresolution (multiscale) methods were included to the transformation domain approaches. Among many multiresolution methods there are simple Laplace pyramids as well as wavelet transforms. In the paper multistage image fusion scheme was used to generate partially and final aggregated image. The fusion performed using simple method based on consecutive levels of Laplace (LAP) [8] and more sophisticated solution using discrete wavelet transformations (DWT) [6, 5].

In the DWT method the discrete wavelet transform is used to obtain hierarchical structure. Depending on the level of transform several sets of details are generated by applying low-pass filtering to the image. Approximation is obtained by downscaling and high-pass filtering. In other words there are four subimages, corresponding to filter outputs: low–low (LL), low–high (LH), high–low (HL), and high–high (HH) bands (Fig. 5). Applying filters recursively to the LL image, the desired number of transform levels is achieved. The decomposition with DWT is performed for all input images. Corresponding details on consecutive levels are aggregated using chosen fusion rule. Similar situation is for the approximations at the last level of decomposition. In this case fusion rule can be different as for the details. The output image is generated by applying inverse DWT to the aggregated decomposed image. The main advantage of DWT fusion technique is the better localization of low frequency components, while the drawback is the high computational load, especially when more than two images are combined.

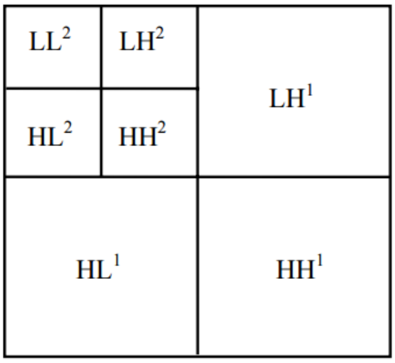


Fig. 5. *2-D DWT structure with labeled sub-images in the two levels decomposition*

The hierarchic approach based on the Laplace pyramid (LAP) [8] decomposes each input image by recursive low-pass filtering and decimation to obtain Gaussian pyramid. In order to reduce the large amount of unwanted redundant information that is stored Gaussian pyramid, it is needed to find the difference between the adjacent two images and get the band-pass filtered images. This set is the Laplacian Pyramid, and only on the last stage there is no differential image to allow inverse transform. Decomposed images are similarly combined on corresponding levels. Typically on last decomposition level the fusion rule is different as on previous ones. After combination the output image is obtained by applying inverse transform (synthesis).

For DWT based method there are three main parameters that must be specified. First is the type of wavelet. After preliminary research symlet wavelet was selected. Other crucial parameters are fusion rules for details and approximations. In the presented study mean, max and min operators were chosen. In the case of LAP method mean and absolute maximum were selected as the fusion rules. Both rules can be applied at each decomposition level.

3.2. Evaluation of image quality

Due to many different combinations of parameters on each stage of the proposed method the authors decided to use image quality measure in order to find the best way of compression ir image range achieving high image quality.
For objective quality assessment several measures using reference image as well as objective approach (without reference images) were considered. Following measures were used: gray-level local variance (GLLV) [Pech200], histogram entropy (HISE) [12], Tenengrad variance (TENV), energy of gradient (GRAE), Brenner's focus measure (BREN) [10], Tenegrad (TENG) [12], Steerable filters-based metrics (SFIL) [13], histogram range (HISR) [14], difference between maximal and minimal values (MAXMIN) and Structural similarity index (SSIM) [9] is based on comparisons of local luminance (temperature), contrast and structure between reference image and fused image that is evaluated. The SSIM computation is carried out on a local window by dividing the whole image into image blocks of N x N size. For two images the SSIM is defined as:

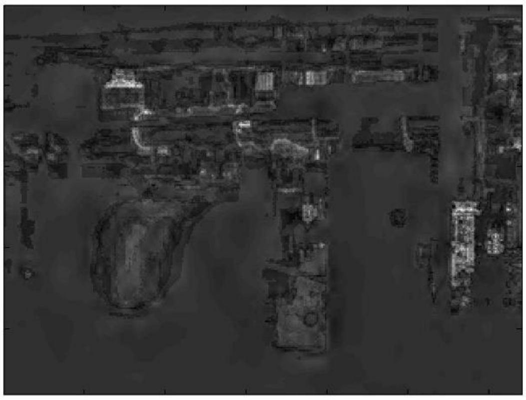
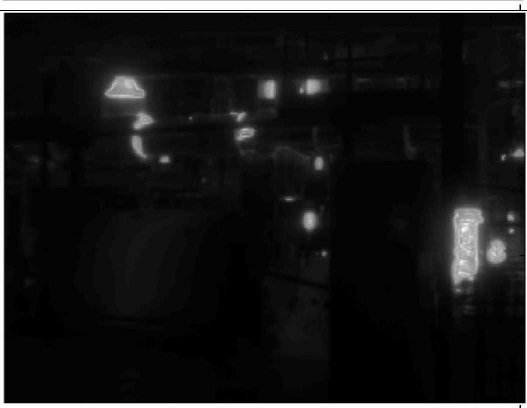
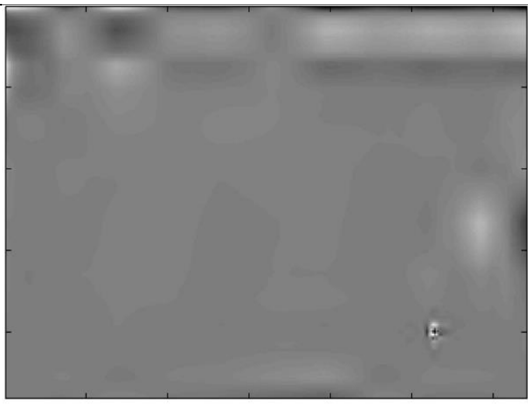
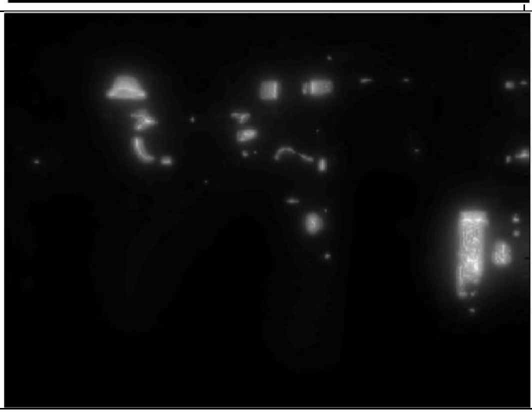
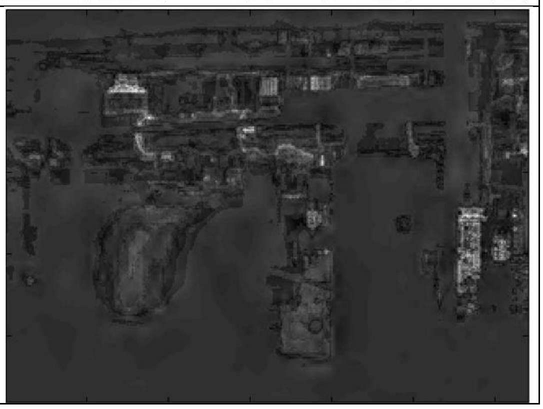
$$SSIM(\boldsymbol{x},\boldsymbol{y}) = \frac{(2\mu_x\mu_y+C_1)(2\sigma_{xy}+C_2)}{(\mu_x^2+\mu_y^2+C_1)(\sigma_x^2+\sigma_y^2+C_2)} \tag{2}$$

Where: where μ_x, μ_y are the mean values, σ_x, σ_y are variance, σ_{xy} is covariance and C_1, C_2 are small constants.

4. The Results

According to above described method considered infrared image was processed and evaluated. Results were shown in Tab. 1. Because of the large number of obtained results, in the table 1 only images for which values of the considered image quality measures were highest are gathered. The results were compared visually taking into account the type of applied image fusion method, number of secondary images and the value of the weighting function parameter β. As one can expect the best results were obtained when the number of generated secondary images was greater and weighting function parameter β is in range from 0.2 to 0.7. From image fusion point of view the method based on wavelet transform (DWT) allows obtain compressed images with better quality than fusion method based on Laplace pyramid. The resulting images have allowed also evaluate applied image quality measure. The measures GRAE (energy of gradient), BREN (Brenner's focus measure), SFIL (Steerable filters-based metrics) and SSIM (Structural similarity index) indicate images which quality is in accordance with the subjective evaluation of the authors. Exemplary quite good image presented in table 1 in row SFIL and column DWT was obtained after application a following aggregation scheme: first LAI image was generated as the result of applying aggregation on the set of LSSI images, where min operator was chosen to combine approximations coefficients and as well as details coefficients, next to obtain HAI image similar procedure was performed, but in this case max operator was used to combine approximations coefficients and max operator was applied to details coefficients. Finally LHAI image was generated by combining LAI and HAI images where the image reconstruction was made using max operator for approximations coefficients and max operator for details coefficients. Considered 30 secondary images generated on the basis of log-sig function with parameter 0.7.

Table 1. *Results of application of the proposed method ordered according to the highest values of the image quality measures*

Quality measure	Image fusion method	
	LAP	DWT
GLLV		
HISE		
TENV		

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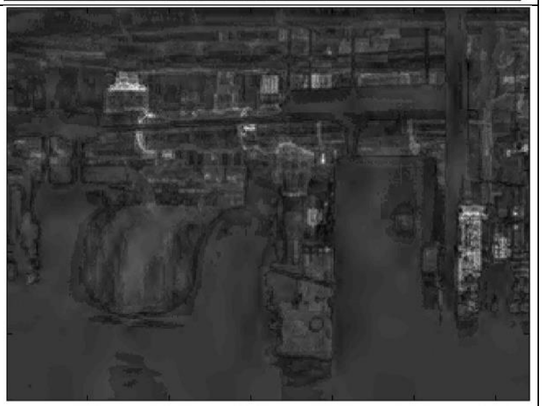
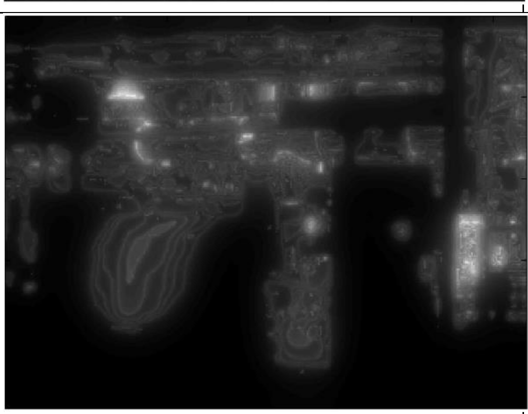
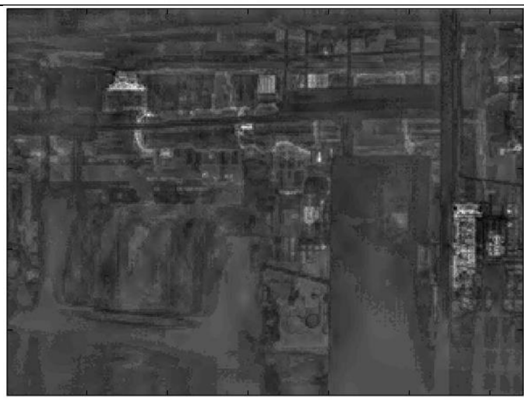
GRAE		
BREN		
TENG		
SFIL		

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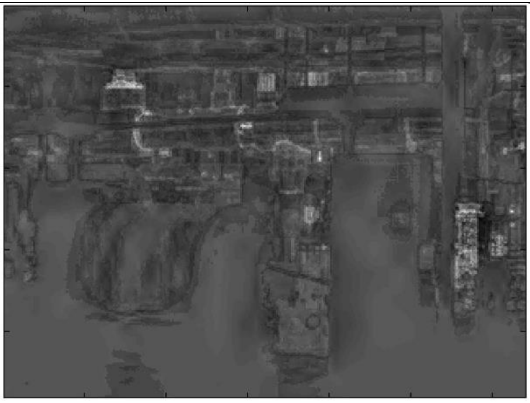
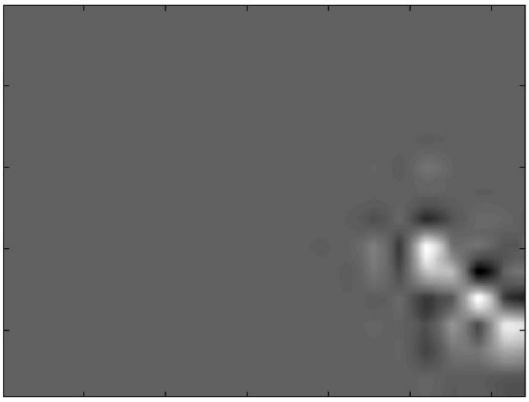
HISR		
MAX		
MIN		
SSIM		

5. Conclusions

The method presented in the paper is on the preliminary stage of development, but even in this phase it is possible to compress high dynamic range of the infrared image simultaneously revealing details previously hidden on the original image. Obtained results strongly depend on type and parameters of weighting function and number of secondary images generated using the function. Also image fusion method and aggregation rules have strong influence on final image what is very good visible in presented results. It was observed that different combination of such operators like mean, max and min usually gives satisfied results. Taking into account content of final images there are a lot details revealed during aggregation of secondary images however for human observer it could be difficult for interpretation. In the best final images not revealed some details due to insufficient number of generated secondary images and type weighting function. Additional investigation confirmed that belter solution could be application of exponential and logarithmic function in order to generate of high and low set of secondary images.

Further research will be focused on optimization of weighting function and number of secondary images. Simplification of image fusion algorithm should also be taken into consideration in order to speed up processing time. Open problem is assessment of image quality. The images indicated by quality measures applied during the research omitted some final images which quality from authors point of view was much better than the best image indicated by value of image quality measure.

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