Contrast Enhancement in Video Sequences Using Variable Block Shape Adaptive Histogram Equalization

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Abstract

This paper describes a new method for enhancing the local contrast of high dynamical range images on conventional low dynamical range displays. We use the mean shift clustering algorithm to segment the image and enhance segments using contrast limited adaptive histogram equalization (CLAHE) in combination with a new kernel based interpolation technique. Our main application is the enhancement of welding image sequences, but we tested our method on a larger image database. Experiments demonstrate improvements over the traditional CLAHE based image enhancement.

1. Introduction and related work

Natural images span a very high dynamic range of intensities. High dynamic range (HDR) images are more and more frequently available in computer graphics and image processing applications [1]. To perform image analysis in natural images, the human visual system is able to adapt to a huge dynamic range of illuminations. However, the dynamic range of image rendering devices, such as camera displays, TV monitors or printers, is limited to a few dozens. This number depends on illumination and also on local image content. Even in a low dynamic range (LDR) image, with only 256 levels of gray, many low contrast details remain unperceived. While most of them are irrelevant for the image analysis task at hand, some may contain essential information. Medical image analysis is one of the typical applications facing the problem of low contrast detail visibility. A broad spectrum of medical images, such as radiographs, CT images, MRI images etc., having dynamic ranges of 10 to 12 bits contain features separated by only a few levels that need to be made visible.

This work was motivated by the problem of contrast enhancement in HDR video sequences obtained in welding applications [2], but we test our method on a broader range of images. Our contrast enhancement approach is based on the mean shift segmentation [3], in order to identify objects or meaningful parts of objects. Subsequently, detail perception within each segment is enhanced by a modified version of the contrast limited adaptive histogram equalization algorithm [4].

Early work on contrast enhancement was influenced by the multiplicative model of image formation:

$$I(x,y) = L(x,y)R(x,y) \tag{1}$$

where L stands for image illuminance, and R for image reflectance. The largest variations in a HDR image are supposed to come from the illuminance function. Image illumination is supposed to vary slowly across the image, while reflectance encodes object shape and local detail, thus is changing fast. The two components can be additively separated by taking the logarithm of the image, then high pass filtering compresses the dynamic range of the illluminance function and enhances shape details. This is the main idea of the homomorphic filtering. More recently, wavelet based approaches [5] enhance the local information in a multiresolution framework. Wavelets and pyramids are multiresolution representations with strong connections to human visual system models. However, transform domain contrast enhancement has been shown to produce undesirable effects, like halo or contrast inversion [6]. The authors propose instead a gradient domain processing method for contrast enhancement. By attenuating the magnitudes of the large gradients, the dynamic range of the image is compressed,

while preserving fine details. A similar approach, based on a more extensive use of human visual models, is described in [7].
Histogram equalization (HE) is one of the most widely used contrast enhancement techniques [8]. The normalized histogram of a monochromatic image is defined by the equation

$$P_r(k) = \frac{n_k}{N} \tag{2}$$

where n_k represents the number of pixels with gray level k and N is the total number of pixels in the image and the columns of the normalized histogram, $P_r(k)$, are probabilities of gray levels.
Suppose the gray levels are normalized to r_k such that

$$0 \le r_k \le 1 \tag{3}$$

The gray scale transformation defined by

$$s_k = T(r_k) = C_r(k) = P_r(r \le r_k) = \sum_{i=0}^{k} P_r(i) \tag{4}$$

produces an output image with gray levels s_k having a uniform distribution between 0 and 1. The gray scale transform needed is the cumulative distribution function of the original image. Since $C_r(k)$ is non-decreasing, the transform is monotonic, that is gray level order relation between pixels is preserved.
The cumulative distribution of the output levels, s, is linearly increasing with s,

$$C_s(k) = P_s(s \le s_k) = \sum_{i=0}^{k} P_r(i) = s_k \tag{5}$$

hence, the distribution of s is uniform. If all probabilities are equal, the image entropy

$$H(I) = -\sum_k P_s(k) \log P_s(k) \tag{6}$$

is maximized. From the information theory point of view, the information provided by such an image, with uniform histogram, is maximized. This technique tends to stretch the contrast of gray levels occurring more frequently, while reducing the contrast of less frequently occurring gray levels. Global histogram equalization is simple and fast but its contrast enhancement effect is relatively low and may produce poor results in several cases. For example, a big and uniform background can cause a wash out effect [9]. Details occupying a small area may disappear.
To overcome the limitations of global HE, and to adapt better to local image content, local HE can be used. In this case, a rectangular image block is defined around each pixel and the gray level of the pixel is transformed by the HE algorithm applied to its block. The procedure, called local HE or adaptive histogram equalization (AHE) [10], is repeated for each pixel, enforcing a high contrast in each region. A major drawback of AHE is its huge computational burden. Non-overlapped sub-block HE can be used to reduce the computational cost of the method, while remaining adaptive to local image content. In this version, all pixels from a block are transformed according to the same histogram equalization process. Due to the fact that adjacent pixels from different blocks are mapped with different transforms, a block-artefact over the image may occur in some regions. This drawback can be alleviated by interpolating the transforms of neighbouring blocks [11] or by using partially overlapped sub-blocks [12].
Full histogram equalization may be undesirable in image regions with narrow gray level distributions, because similar gray levels are mapped to significantly different gray levels and the image noise is highly amplified. A useful approach to this problem is to limit the contrast amplification produced by AHE [13]. The approach, abbreviated as CLAHE, from “Contrast Limited Adaptive Histogram Equalization” is widely used in current works. The main idea of CLAHE is to limit the slope of the cumulative distribution function of the enhanced image to a maximum value.

2. Variable block shape adaptive histogram equalization

The goal of the contrast enhancement method proposed in this section is to improve the visibility of meaningful image details in HDR video sequences. Our main application is the enhancement of welding images captured by HDR video cameras [14]. The images have to be projected on a LDR display mounted on the welding helmet and to provide a better perception of relevant image details needed to carry out the welding task. Nevertheless, we believe that

our results may be useful in a broader spectrum of applications, including biomedical image analysis.
We model the image as a union of objects. Complex objects may be composed of more simple parts. Contrast enhancement techniques based on AHE arbitrarily divide the image into rectangular blocks and compute an image transform based on the content of the block. Some blocks may contain image parts belonging to many objects, while others may be included in a homogeneous area belonging to a unique object. Therefore the information content of the blocks varies widely. On one hand, homogeneous blocks tend to be over-enhanced by histogram equalization, with the result of excessive noise amplification. On the other hand, some useful details with low spatial extent may be lost after histogram equalization in high contrast blocks, as noticed by many researchers.
In this work we propose to form variable shape image blocks for contrast enhancement based on histogram equalization. The image blocks are obtained by mean shift segmentation. A block diagram of the proposed variable block shape adaptive histogram equalization (VBSAHE) for contrast enhancement is given in figure1.

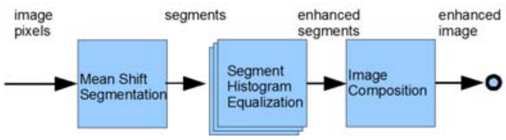

Figure1: VBSAHE concept

Expected benefits from using variable shape image blocks are:

- Generally segmentation generates blocks with borders following object borders. Consequently objects tend to be enhanced individually.
- Since the mean shift segmentation tends to form regions with similar variance, the contrast enhancement obtained is more uniform.
- Small image parts with fairly high contrast are preserved by segmentation and enhanced properly.

The mean shift segmentation algorithm clusters neighboured pixel which converge to similar modes. The cluster algorithm is done by mode linking where in the case of grayscale images the grayscale distance of the modes assigned to neighboured pixel must lay within a bounded deviation. So a small grayscale distance effects in more segments while a higher grayscale distance effects into a lower amount of segments.
The assignment of modes can be done by calculating the new trace point

$$x_{new} = \frac{\sum_{i=1}^{N} \vec{x}_i g\left(\left\|\frac{\vec{x}_{old}-\vec{x}_i}{h}\right\|^2\right)}{\sum_{i=1}^{N} g\left(\left\|\frac{\vec{x}_{old}-\vec{x}_i}{h}\right\|^2\right)} \tag{7}$$

if the difference between the old and the new value is greater than a lower bound

$$\|\vec{x}_{old} - \vec{x}_{new}\| \leq \epsilon \tag{8}$$

then set $\vec{x}_{old} = \vec{x}_{new}$ and calculate the new trace point else stop the convergence calculation and assign the resulting $\vec{x}_{new}$to the initial starting point.
After segmenting the image using the non-parametric adaptive gradient ascent method mean shift, the segments are individually enhanced by contrast limited histogram equalization as it is used by the CLAHE algorithm. The contrast limitation factor (cl) limits the maximum slope of the pixel mapping function. Hereby the number of pixel count for every bin of the mapping histogram is clipped to an upper bound. The upper bound is the product of contrast limit and the average histogram bin count. Pixels exceeding the upper bin count are uniformly redistributed to the mapping histogram [13]. The contrast limitation avoids the amplification of noise in flat areas which contain low information as it is known for pure histogram equalization.
If the individual enhancement of the segments is calculated, the image needs to be recomposed to a new image. As known from the CLAHE algorithm an interpolation process is needed to avoid rough edges between the segments. The CLAHE uses an interpolation scheme based on the distance of the pixel to the three nearest neighboured tiles. As the tiles are replaced by segments, which are individual in shape and size, this approach fails. We propose to use a kernel based approach, where the mapping function for a pixel is a weighted sum of the surrounding histogram mapping functions of segments. The proximity can be weighted by a kernel function e.g. a radial kernels based on the normal or Epanechnikov profile.

The image *I* consists of a set of positions

$$X = \{\vec{x} | \vec{x} \in I\} \tag{9}$$

and the assigned pixel values $p(\vec{x})$

After segmentation the image consist of segments

$$S = \{S_1, S_2, \ldots, S_k\} \tag{10}$$

where the segments cover all (pixel-) positions in the image

$$X = \bigcup_{i=1}^{k} S_i \tag{11}$$

For a pixel value *p* at the position

$$\vec{x} = (u, v) \in S_i, \; i \in \{1 \ldots k\} \tag{12}$$

an histogram mapping function $s_i(p)$ is surjectively assigned for this position

$$\breve{p}(u, v) = s_i(p(u, v)) \tag{13}$$

so that $s_{i,\vec{x}_n}()$ designates the assigned histogram mapping function at position $\vec{x}_n$.

To avoid harsh edges due to the segments border, the new improved pixel value $\tilde{p}(u, v)$ for the composed image is calculated by an interpolation of the histogram mapping functions in the kernel bounded proximity

$$\Delta_X = \{x_n | n = 1 \ldots, N\} \tag{14}$$

Analogue to the kernel density estimator a radial kernel (e.g. Epanechnikov, normal or unit kernel) with its centre at the position $\vec{x}_0 \, (u_0, v_0)$ is used.

The weighting value at the position $\vec{x}_n$ with the kernel at position $\vec{x}_0$ given by

$$K(\vec{x}_0, \vec{x}_n) = c_{k,d} k \left(\left\| \frac{\vec{x}_0 - \vec{x}_n}{h} \right\|^2 \right) \tag{15}$$

The new pixel value $\tilde{p}_i(\vec{x}_0)$ is interpolated as a weighted sum depending on the distance and the participating histogram mapping functions s_i for the proximity positions

$$\tilde{p}(\vec{x}_0) = \frac{c_{k,d}}{N \; h^D} \sum_{n=1}^{N} s_{i,\vec{x}_n}(p(\vec{x}_0)) \, k \left(\left\| \frac{\vec{x}_0 - \vec{x}_n}{h} \right\|^2 \right) \tag{16}$$

In the summation only the different histogram mapping functions and the weighting kernel value are changed. An example is given as follows for the new value of a single pixel with three segments S_1, S_2, S_3 in the proximity (see figure 2).

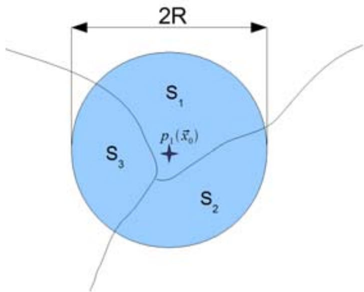

Figure 2 Example for interpolating a new pixel value

The new pixel value for $p(\vec{x}_0)$ is calculated as

$$\begin{aligned} \tilde{p}_1(\vec{x}_0) = \frac{c_{k,d}}{3 \cdot 4R^2} \Bigg(& \sum_{\forall x_n \in S_1} s_1(p_1(\vec{x}_0)) k \left(\left\| \frac{\vec{x}_0 - \vec{x}_n}{2R} \right\|^2 \right) \\ & + \sum_{\forall x_n \in S_2} s_2(p_1(\vec{x}_0)) k \left(\left\| \frac{\vec{x}_0 - \vec{x}_n}{2R} \right\|^2 \right) \\ & + \sum_{\forall x_n \in S_3} s_3(p_1(\vec{x}_0)) k \left(\left\| \frac{\vec{x}_0 - \vec{x}_n}{2R} \right\|^2 \right) \Bigg) \end{aligned} \tag{17}$$

3. Experiments

In this section experiments are described to study the effectiveness of the multi-scale mode filter in edge preserving image smoothing tasks.

To evaluate the behaviour of the VBSAHE algorithm a welding scene image is used as shown in figure 3.

It contains a working scene with the bright burning welding arc and in opposition huge area with low contrast background

Changing the contrast limit (cl) for the histogram equalization as show in figure 4, effects as expected in higher amplification of noise the higher the contrast limit is selected. To choose the standard value of cl=5 gives for the welding image a good trade-off between contrast enhancement and noise amplification

Figure 3: Original welding scene image during welding

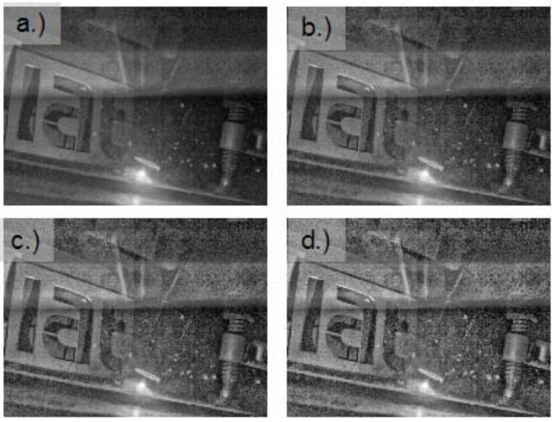

Figure 4: VBSAHE with different Contrast limitation of
a.) cl=3, b.) cl=5, c.) cl=7, d.) cl= 9

Composing the image from the individually enhanced segments depends on the diameter of the interpolating kernel. If the kernel size is chosen small then hard edges between the segments are more visible. Especially artefacts for low color gradient segments remain visible if the interpolation radius is small. In figure 5.a the artefact of the mean shift segmentation are still clearly visible and are minimized the bigger the interpolation kernel is chosen. If the kernel size is bigger than necessary the local contrast diminishes (see figure 5.d).

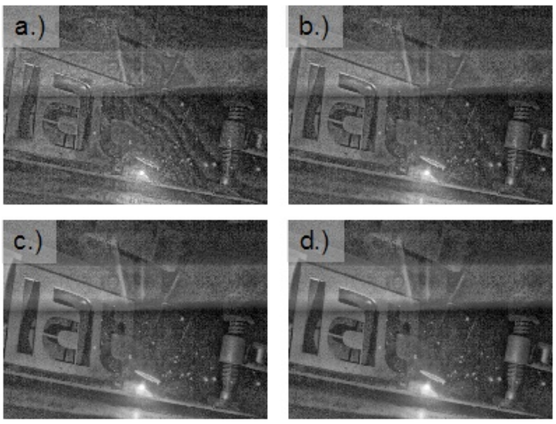

Figure 5: VBSAHE with different kernel size for the interpolation
a.) R=4, b.) R=12, c.) R=28, d.) R= 32

The best result is achieved by using a colour distance for the mode linking of CD=10, a CLAHE typical contrast limitation of cl=5 and an interpolation kernel with the radius R=28 (see figure 6).

Figure 6: Best result of VBSAHE with cl=5, R=28, CD=10

The VBSAHE outperforms the CLAHE algorithm which was applied with a contrast limitation of cl=5 and dividing the image in 64x64 tiles.

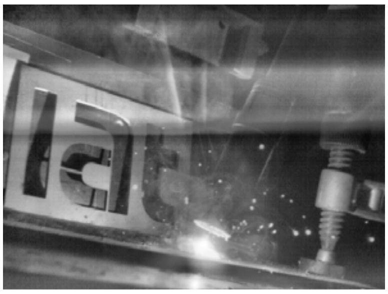

Figure 7: CLAHE applied with cl=5, 64x64 tiles

Better result is given on the right side where the parts of screw clamp are more structured. At the welding arc in the middle is the information not compressed to high values while the environment is better visible (see figure 6, figure 7).
A look onto the histograms in figure 8 gives the impression that CLAHE is shape preserving the original histogram, while the VBSAHE enhances the image resulting to a complete new shape for the histogram. It shows that the VBSAHE is enhancing more independently related to the light conditions than the CLAHE. The interrelation between two different segments is not ensured any more although the information of the image is enhanced.

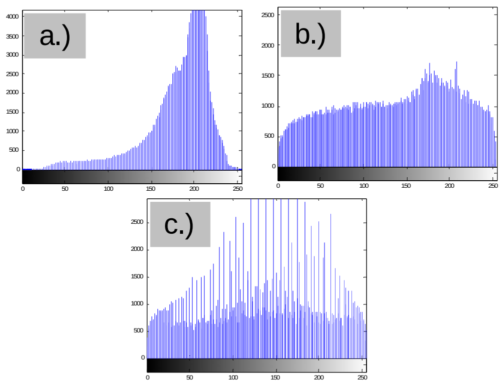

Figure 8: Histogram of a.) Original b.) CLAHE enhanced
c.) VBSAHE enhanced welding scene image

The enhancement for a nature image (see figure 9) with strict borders between clear different background parts, while the object of interest is visible in both parts is given in figure 10.

Figure 9: Original surfer image

After applying the VBSAHE the waves and the hillside with its trees and details like the pattern on the underside of the surf board becomes visible.

Figure 10: VBSAHE with cl=5, R=16 and CD=10

The aerial survey (see figure 11) has highly packed information which must not get lost.

Figure 11: Original aerial survey

The performance of the VBSAHE produces an image where the details like the cars and as well plain areas like the meadow at the bottom right are highly enhanced (see figure 12).

Figure 12: VBSAHE applied with cl=5, R=16, cd=10

The VBSAHE gives good results by adjusting only the interpolation radius for composing the segments to a new image

4. Conclusions

In this work, we presented a new method of contrast enhancement in high dynamic range images. Our technique is a generalization of the contrast limited adaptive histogram equalization technique, working on image segments obtained by the mean shift clustering technique, instead of working on rectangular image blocks. A new image interpolation technique is designed in order to avoid artifacts if segment borders do not coincide with object borders. With the proposed contrast enhancement method, meaningful parts in the image are preserved and enhanced effectively. Comparative tests revealed performance improvements over the traditional contrast limited adaptive histogram equalization.

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