

Image Enhancement by Frequency Analysis

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Abstract. Because of lighting or the quality of CMOS/CCD, poor images are often gained, which greatly affect subjective observation. Image enhancement can improve the contrast of poor image. In our paper, we propose a new image enhancement algorithm based on frequency analysis. A central energy of FFT is utilized for computation of image enhancement factors. A linear mapping is used for image mapping. Finally, some experimental results are shown for illustration of our algorithm advantage.

1 Introduction

With the development of image processing, a lot of image application depends on image quality. However, distorted images or poor images occurred because of poor CCD/CMOS or poor lighting environment. In this case, image enhancement can be used for improve the image quality. Traditional image enhancement normally makes use of histogram equalization. However, this kind of image enhancement method results in colour non-uniformity and illumination inconsistency. Then, gradient histogram's method is applied for image denoising, image deblurring, image restoration etc. [1-11] However, histogram-based is hard to produce rational effects.

In this paper, we propose an image enhancement based on frequency analysis. We find that the central energy of image frequency domain has high relation with image quality. And, we can use a simple mapping function to get enhanced image with central energy computation.

In the rest part of this paper, frequency analysis scheme will be introduced in section 2. Experimental results are provided in section 3. And finally section 4 concludes the paper.

2 Proposed algorithm

In this section, the proposed algorithm will be introduced. Firstly, a non-local mean filter [2] is utilized for image pre-processing. An simple computation of non-local mean is shown as following

$$NL(I) = \sum W(i, j) \cdot I(i, j) \quad (1)$$

Where, W is a weighting coefficients of pixel intensity similarity. Gaussian kernel is adopted for computation of weighted Euclidean distance. After image

filtering, we need to transform the image from spatial domain to frequency domain. Fast FFT is used to realize the transformation, which can be described as following,

$$FFT(I) = \sum_{n=0}^{N-1} I_n \cdot e^{-i2\pi kn/N} \quad (2)$$

Where, N are sample points, which is the power of 2. k is the image pixel index. In order to get central frequency magnitude, vertical and horizontal transformation is used for FFT transformed image. Then, we get a map of central frequency magnitude. In this magnitude map, we can find that images with different quality show different central energy. Finally, in order to represent the central energy, we use a central entropy to formulate, which is described as following,

$$EN(F) = \sum_{i=0}^{255} F_i^v \cdot \log(F_i^v) \quad (3)$$

Where, F is the frequency transformed image. Then a linear mapping should be used for final enhanced image. Here, we use a global linear approximation method to remap original image into enhanced image.

3 Experiments

In this section, different image enhanced results are demonstrated. Our test database utilized surveillance images.

Figure1 shows an image enhanced example using our algorithm. Figure1(a) and Figure 1(b) are original low quality images. And, Figure 1(c) and Figure 1(d) are the image enhanced results. It can be seen that our method performs a good image enhancement with better contrast, which closes to real surveillance scene. Figure 2 is another example, which also illustrate our advantage. In our last example, entrance and underground parking are

shown as following. From all of the experimental results, our algorithm shows better processing effect comparing with original image.



(a)



(b)



(c)



(d)

Figure 1. The effect of image enhancement for surveillance images. a and b are input images, c and d are enhanced results.



(a)



(b)



(c)



(d)

Figure 2. The effect of image enhancement for surveillance images. a and b are input images, c and d are enhanced results.



(a)



(b)



(c)



(d)

Figure 3. The effect of image enhancement for surveillance images. a and b are input images, c and d are enhanced results.

4 Conclusions

In this paper, we presented a frequency domain analysis method inspired by frequency central energy fused a linear mapping. Experiment results demonstrate the benefits of frequency domain analysis advantage.

Acknowledgement

This work was supported by the Opening Project of Shanghai Key Laboratory of Digital Media Processing and Transmission.

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