The Evaluation of Image Enhancement and Restoration Methods

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***Abstract*—This paper is focused on the different image enhancement and image restoration methods. Image enhancement has been regarded as one of the most important vision applications because it can improve the visual effect of images. Image restoration is a method to clear the degraded image to obtain the original image. For years researchers have been working on developing new techniques that can restore the original image from degraded image. In this paper, we adopt seven image enhancement methods including Histogram Equalization (HE), Adaptive Histogram Equalization (AHE), Contrast Limited Adaptive Histogram Equalization (CLAHE), Mean Filtering, Median Filtering, Bilateral Filtering, Gaussian Filtering. Meanwhile, we adopt three image restoration methods including L_0 Sparse Representation, L_0-Regularized, Dark Channel Prior. To evaluate and compare the performance of these ten methods, we apply one evaluation measures - Peak Signal to Noise Ratio (PSNR).**

I. Introduction

Image enhancement is the process that consists of collection of techniques which are used to improve the visualization of the image for the human analysis. Image enhancement means increasing the appearance of an image by increasing the dominance of some features and decreasing ambiguity between different regions of the image. Image enhancement has vital role in many fields likes high definition TV (HDTV), X-ray processing, motion detection, remote sensing and in studying medical images. Image enhancement is mainly increasing the observation of information in images for individual viewers and providing improved input for other image processing methods. The principal aim of image enhancement is to alter attributes of an image to make it more appropriate for a given job and a specific observer. During this process, one or more attributes of the image are altered. In recent years, the focus of image enhancement research is to enhance the edge or texture detail information of the image, rather than to improve the dark part of the image.

Images in the real world are subject to various forms of degradation during image capture, acquisition, storage, transmission and reproduction. Images are everywhere in our daily life. This is not only because image is a widely used medium of communications, but also because it is an easy and compact way to represent the physical world. Processing of digital images with the help of digital computers known as Digital Image Processing. Image restoration is a method to clearing the degraded image to obtain the original image. For years researchers have been working in developing new techniques that can restore the original image from degraded image.

In recent years, image enhancement and image restoration are the basic methods of dealing with image problems, which can be applied to different problems, such as image deblurring, image dehazing, etc. The aim of this paper is to demonstrate the different types of methods for image enhancement and image restoration.

II. Image Enhancement Methods

In this section, we briefly review the following five image enhancement methods:

- Histogram Equalization (HE)[1]
- Adaptive Histogram Equalization (AHE)[1]
- Contrast Limited Adaptive Histgram Equalization (CLAHE)[1]
- Mean Filtering[1]
- Median Filtering[1]
- Bilateral Filtering[1]
- Gaussian Filtering[1]

A. Histogram Equalization (HE)[1]

Histogram equalization is a spatial domain method that produces output image with uniform distribution of pixel intensity means that the histogram of the output image is flattened and extended systematically [2, 4]. This approach customarily works for image enhancement paradigm because of its simplicity and relatively better than other traditional methods. We acquire the probability density function (PDF) and cumulative density function (CDF) via the input image histogram. Apply these two functions PDF and CDF for replacing the input image gray levels to the new gray levels, and then we generate the processed image and histogram for the resultant image. And when we compare the histogram of input image with the histogram of processed image, we found that the gray levels are stretched and depressed systematically. Consequently, we found that the histogram of the output image is systematically distributed. During histogram equalization methods the mean brightness of the processed image is always the middle gray level without concerning of the input mean. This procedure is not very convenient to be enforced in consumer electronics, such as television, by the reason of that the method tends to cause the irrelevant visual deterioration like the concentration effect. The particular explanation for this issue is to conquer this weakness is by perpetuating the mean brightness of the input image indoor the output image.

Algorithm Steps:

(1) record the number of times the image gray value is 0-255

(2) calculate the gray histogram of original image

(3) calculate the CDF, and further calculate gray transformation table

(4) according to the gray level transformation table, the gray level of the original image is mapped to a new gray level.

B. Adaptive Histogram Equalization (AHE)[1]

HE uses the same histogram transform for the pixels of the whole image, and the algorithm works well for images where the pixel values are more balanced. Then, if the image contains a portion that is darker or brighter than the other areas of the image, the contrast in these parts will not be effectively enhanced. Adaptive Histogram Equalization (AHE) is a computer image processing technique used to enhance the contrast of an image. Unlike the normal histogram equalization algorithm, AHE algorithm changes the image contrast by calculating the local histogram of the image and then redistributing the brightness. Therefore, the algorithm is more suitable for improving the local contrast of the image and to get more image detail.

This is an extension to traditional Histogram Equalization technique. It enhances the contrast of images by transforming the values in the intensity image. Unlike HISTEQ, it operates on small data regions (tiles), rather than the entire image. Each tile's contrast is enhanced, so that the histogram of the output region approximately conforms to the specified histogram. The neighboring tiles are then combined using bilinear interpolation in order to eliminate artificially induced boundaries. The contrast, especially in homogeneous areas, can be limited in order to avoid amplifying the noise which might be present in the image.

Its advantage is more suitable for improving the local contrast of the image and obtaining more image detail. But it also over-amplifies the noise of the same area in the image.

C. Contrast Limited Adaptive Histgram Equalization (CLAHE)[1]

The biggest difference between CLAHE and AHE is that the former limits the contrast, this feature can also be applied to the global histogram equalization, but in fact it is rarely used. In CLAHE, each pixel neighborhood has a contrast limiting value, resulting in a corresponding transform function that is used to reduce the noise in the AHE, which is primarily achieved by limiting the contrast enhancement in the AHE. The enhancement of the neighborhood noise is mainly caused by the slope of the transformation function. Since the noise in the neighborhood of the pixel is proportional to the CDF of the neighborhood, it is also proportional to the value of the neighborhood histogram at the center pixel position. The reason why CLAHE can limit the contrast of image is that it prunes the histogram at the specified threshold before calculating the CDF, which not only limits the slope of the CDF but also limits the slope of the transform function.

Algorithm Steps:

(1) Obtain all the inputs: image, number of regions in row and column directions, number of bins for the histograms used in building image transform function (dynamic range), clip limit for contrast limiting (normalized from 0 to 1)

(2) Pre-process the inputs: determine real clip limit from the normalized value if necessary, fill the image before splitting it into regions

(3) Process each contextual region (tile) thus producing gray level mappings: extract of a single image, plot a histogram for this region using the specified number of bins, clip the histogram using clip limit, create a mapping (transformation function) for this region

(4) Interpolate gray level mappings in order to assemble final CLAHE image: extract cluster of four neighbouring mapping functions, solve image region partly overlapping each of the mapping tiles, extract a single pixel, apply four mappings to that pixel, and interpolate between the results to obtain the output pixel; repeat over the entire image

And CLAHE uses interpolation to speed up computation. CLAHE overcome the problem of over amplification of AHE noise.

D. Mean Filtering[1]

Image filtering is an important part of image enhancement, Image filtering is used to remove noise, sharpen contrast, highlight contours and detect edges. Image filters can be classified as linear or nonlinear. Linear filters also know as convolution filters as they can be represented using a matrix multiplication. Thresholding and image equalization are the example of nonlinear operations, such as the median filter.

Mean filtering regard as a method of 'smoothing' images by reducing the amount of intensity variation between neighbouring pixels. The Mean filtering works by moving through the image pixel by pixel, replacing each value with the average value of neighbouring pixels, and including itself. But there are some potential problems. A single pixel with a very unrepresentative value can significantly affect the average value of all the pixels in its neighbourhood. When the filter neighbourhood straddles an edge, the filter will interpolate new values for pixels on the edge and so will blur that edge. This may be a problem if sharp edges are required in the output.

E. Median Filtering[1]

Median filter is a kind of effective noise suppression of nonlinear signal processing technology based on the statistical theory. The basic principle of median filter is to use the median value instead of each point of a neighborhood of the points in a digital image or sequence, and make the pixel value close to the true value, thereby isolated noise points are eliminated. The method adopts 2D sliding template structure is sorted according to the pixel in the pixel value size, and generating monotone two-dimensional data (ascending or descending) sequence. Two dimensional median filter output is $g(x,y) = med\{f(x-k, y-l), (K, l \in W)\}$, which $f(x,y), g(x,y)$ respectively is the original image and the processed image. W is a two-dimensional template, usually 2*2, 3*3 area, can also be a different shape, such as linear, circular, cross shaped, ring shaped, etc..

Median filtering is that a nonlinear method used to remove noise from images. It is widely used as it is very effective at removing noise while preserving edges. The median filter works by moving through the image pixel by pixel, replacing each value with the median value of neighbouring pixels. The pattern of neighbours is called the ”window”, which slides, pixel by pixel over the entire image pixel, over the entire image. The median is calculated by first arranging all the pixels from the window in numerical order, and then replacing the pixel being considered with the median pixel value. Median filter has the performance of denoising, which can eliminate isolated noise points and can be used to reduce the random interference, but the edge is not fuzzy.

F. Bilateral Filtering[1]

The bilateral filter is a non-linear technique that can blur an image while respecting strong edges. Its ability to decompose an image into different scales without causing haloes after the modification has made it ubiquitous in computational photography applications such as tone mapping, style transfer, relighting, and denoising. Bilateral filtering is a technique to smooth images while preserving edges. The bilateral filter is also defined as a weighted average of nearby pixels, in a manner very similar to Gaussian convolution. The difference is that the bilateral filter takes into account the difference in value with the neighbors to preserve edges while smoothing. The key idea of the bilateral filter is that for a pixel to influence another pixel, it should not only occupy a nearby location but also have a similar value.

The formalization of this idea goes back in the literature to Yaroslavsky [1], Aurich and Weule [2], Smith and Brady [3] and Tomasi and Manduchi [4]. The bilateral filter, denoted by BF, isdefined by:

$$BF[I]_p = \frac{1}{W_p} \sum_{q \in s} G_{\sigma_s}(||p-q||) G_{\sigma_r}(|I_p - Iq|) I_q \quad (1)$$

where normalization factor W_p ensures pixel weights sum to 1.0:

$$W_p = \sum_{q \in s} G_{\sigma_s}(||p-q||) G_{\sigma_r}(|I_p - Iq|) \quad (2)$$

Parameters σ_s and σ_r will specify the amount of filtering for the image I. Equation (1) is a normalized weighted average where G_{σ_s} is a spatial Gaussian weighting that decreases the influence of distant pixels, $G_{\sigma_r}$is a range Gaussian that decreases the influence of pixels q when their intensity values differ from I_p.

G. Gaussian Filtering[1]

Gauss filter is a kind of linear smoothing filter, which is suitable for eliminating the noise of the Gauss and widely used in image processing. Gauss filter is a kind of linear smoothing filter based on the shape of the function of the Gauss. The Gauss smoothing filter is very effective in suppressing the noise obeying normal distribution.One dimensional zero mean Gauss function:

$$G(x) = e^{-\frac{x^2}{2\sigma^2}} \quad (3)$$

The Gauss distribution parameter σ determines the width of the Gauss function. For image processing, two dimensional zero mean discrete Gauss function is used as smoothing filter.

Two dimensional Gauss function:

$$G_0(x,y) = Ae^{-\frac{(x-\mu_x)^2}{2\sigma_x^2} - \frac{(y-\mu_y)^2}{2\sigma_y^2}} \quad (4)$$

If you use the ideal filter, it will ring in the image. With the Gaussian filter, the system function is smooth and avoids the appearance of ringing. In general, Gaussian filtering is the process of weighting the entire image, and the value of each pixel is obtained by weighted average of the other pixel values in the neighborhood and the neighborhood. The specific operation of Gaussian filtering is to scan each pixel in the image with a template (or convolution, mask), instead of the value of the central pixel of the template, using the weighted average gray value of the pixels in the neighborhood determined by the template.

III. Image Restoration Methods

In this section, we briefly review the following three image restoration methods:

- L_0 Sparse Representation[5]
- L_0-Regularized[6]
- Dark Channel Prior[7]

A. L_0 Sparse Representation[5]

Xu et al. [5] shows the success of previous maxi-mum a posterior (MAP) based blur removal methods partlystems from their respective intermediate steps, which implicitly or explicitly create an unnatural representation containing salient image structures. They propose a generalized and mathematically sound L_0 sparse expression, together with a new effective method, for motion deblurring. Their system does not require extra filtering during optimization and demonstrates fast energy decreasing, making a small number of iterations enough for convergence. It also provides a unified framework for both uniform and non-uniform motion deblurring.

We denote by x the latent image and y the blurred observation. x and y are in their vector forms. The discrete blur model for camera shake can be expressed as

$$y = \sum_m k_m H_m x + \epsilon \quad (5)$$

where x, y, and noise ϵ are $N * 1$ vectors. N is the number of pixels in the image. m indexes camera pose samples. $H_m$is a $N * N$ transformation matrix, which corresponds to either camera rotation or translation for pose m. k_m denotes the time that camera pose m lasts and is a weight in this function. Eq. (5) models the blurred image as summing unblurred images from all camera poses, which approximates continuous integral on light receival for each pixel.

In camera translation, they similarly substitute M_m for H_m in Eq. (5), which yields

$$\sum_m k_m M_m x = B_m x + A_M k \tag{6}$$

where B_M and A_M are block Toeplitz with Toeplitz blocks (BTTB) matrices, since camera translation is linear translation invariant (LTI).

In this method, they define a new sparisty $\phi_0(.)$ loss funtion, which can effectively approximate L_0 sparsity during iterative optimization. Given an input image z, it regularizes the high frequency part by manipulating gradient vectors $\alpha * z$, where $* \in h, v$ denoting two directions, for each pixel i. The function is defined as

$$\phi_0(\alpha * z) = \sum_i \phi(\alpha * z_i) \tag{7}$$

Then, estimate the blur kernel from the input image is

$$\min_{(x,k)} \left\{ \| \sum_m k_m M_m x - y \|^2 + \lambda \sum_{* \in h,v} \phi_0(\alpha * x) + \gamma \|k\|^2 \right\} \tag{8}$$

It also enables fast kernel estimation using FFTs with the quadratic form. $\phi_0(\alpha * x)$ is the new regularization term, which is instrumental in thier method, to guide kernel estimation.

The computed map x is not the final latent natural image estimate due to lack of details. In the final step, they restore the natural image by non-blind deconvolution given the final kernel estimate. A Hyper-Laplacian prior with $L_{0.5}$ norm regularization [15] is used. Image restoration for both the uniform and non-uniform blur is accelerated by FFTs.

B. L_0-Regularized[6]

Pan et al. [6] propose a simple yet effective L_0-Regularized prior based on intensity and gradient for image deblurring. The proposed image prior is motivated by observing distinct properties of images. Based on this prior, they develop an efficient optimization method to generate reliable intermediate results for kernel estimation. The proposed method does not require any complex filtering strategies to select salient edges which are critical to the state-of-the-art deblurring algorithms.

The proposed L_0 intensity and gradient prior is based on the observation that characters and background regions usually have near uniform intensity values in clean images without blurs.This intensity property is generic for text images and used as one regularization term in their formulation. For an image x, they define

$$P_t(x) = \|x\|_0 \tag{9}$$

where $\|x\|_0$ counts the number of nonzero values of x. With this criterion on pixel intensity, clean and blurred images can be differentiated.

Gradient priors are widely used for image deblurring as they have been shown to be effective in suppressing arti facts. As the intensity values of a clean image are close to two-tone, the pixel gradients are likely to have a few nonzero values.Thus they use L_0-regularized prior, $P_t(\bigtriangledown x)$, to model image gradients.

The image prior for text image deblurring is defined as

$$P(x) = \sigma P_t(x) + P_t(\bigtriangledown x) \tag{10}$$

where σ is a weight. Although $P(x)$ is developed based on the assumption that background regions of a image are uniform, it show that this prior can also be applied to image deblurring with complex backgrounds.

The proposed prior $P(x)$ is used as a regularization term for deblurring,

$$\min_{(x,k)} \|x * k - y\|^2 + \gamma \|k\|_2^2 + \lambda P(x) \tag{11}$$

In [7] all the experiments, they set $\lambda = 4e3, \gamma = 2$, and $\sigma = 1$, respectively.

C. Dark Channel Prior[7]

Pan et al. [7] present a simple and effective blind image deblurring method based on the dark channel prior. Their work is inspired by the interesting observation that the dark channel of blurred images is less sparse. While most image patches in the clean image contain some dark pixels, these pixels are not dark when averaged with neighboring high-intensity pixels during the blur process. This change in the sparsity of the dark channel is an inherent property of the blur process, which they both prove mathematically and validate using training data. Therefore, enforcing the sparsity of the dark channel helps blind deblurring on various scenarios, including natural, face, text, and low-illumination images. However, sparsity of the dark channel introduces a non-convex non-linear optimization problem. They introduce a linear approximation of the min operator to compute the dark channel. Our look-up table-based method converges fast in practice and can be directly extended to non-uniform deblurring. Extensive experiments show that their method achieves state-of-the-art results on deblurring natural images and compares favorably methods that are well-engineered for specific scenarios.

For an image J, the dark channel [8] is defined by

$$D(J)(x) = \min_{y \in \Omega(x)} \left(\min_{c \in r,g,b} J^c(y) \right) \tag{12}$$

where x and y denote pixel locations; $\Omega(x)$ is an image patch centered at x; and J^c is the c-th color channel. If J is a gray-scale image, we have $\min_{c \in r,g,b} J^c(y) = I(y)$. The dark channel prior is mainly used to describe the minimum values in an image patch. He et al. [8] observe that the dark channel of outdoor, haze-free images is almost zero. Pan et al.[7] find that most, although not all, elements of the dark channel are zero for natural images. However, most elements in the dark channel of blurred images are nonzero. To explain why the dark channel of blurred images are less sparse, we derive some properties of the blur (convolution) operation. For discrete signals (images), convolution is defined as the sum of the product of the two signals after one is reversed and shifted

$$B(x) = \sum_{z \in \Omega(k)} J(x)[\frac{s}{2}] - z)k(z) \quad (13)$$

where $\Omega(k)$ and s denote the domain and size of blur kernel k, $k(z) \geq or \geq 0$, $\sum_{z \in \Omega(k)} k(z) = 1$, and [.] denotes the rounding operator.

Pan et al.[7] use the $\|D(J)\|_0$ norm to measure sparsity of dark channels. We add this constraint to a standard formulation for image deblurring as

$$\min_{(J,k)} \|J * k - y\|_2^2 + \gamma\|k\|_2^2 + \lambda\|D(J)\|_0 + \mu\| \bigtriangledown J\|_0 \quad (14)$$

where the first term imposes that the convolution output of the recovered image and the blur kernel should be similar to the observation; the second term is used to regularize the solution of the blur kernel; the third term on image gradients retains large gradients and removes tiny details; γ, λ and μ are weight parameters.

In all experiments, they set $\lambda = \mu = 0.004, \gamma = 2$, and the neighborhood size to compute the dark channel in (12) to be 35 (please see the supplemental material for analysis). They empirically set max_iter = 5 as a trade-off between accuracy and speed.

IV. Evaluation

In this paper, I evalutate the 10 methods by using the evaluation index-Peak signal-to-noise ratio (PSNR). Peak signal-to-noise ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale.

PSNR is most commonly used to measure the quality of reconstruction of lossy compression codecs (e.g., for image compression). The signal in this case is the original data, and the noise is the error introduced by compression. When comparing compression codecs, PSNR is an approximation to human perception of reconstruction quality. Although a higher PSNR generally indicates that the reconstruction is of higher quality, in some cases it may not. One has to be extremely careful with the range of validity of this metric; it is only conclusively valid when it is used to compare results from the same codec (or codec type) and same content. PSNR is most easily defined via the mean squared error (MSE). Given a noise-free $m * n$ monochrome image I and its noisy approximation K, MSE is defined as:

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - K(i,j)]^2 \quad (15)$$

The PSNR (in dB) is defined as:

$$PSNR = 10 * log_{10}(\frac{MAX^2}{MSE}) \quad (16)$$

Here, MAX is the maximum possible pixel value of the image. When the pixels are represented using 8 bits per sample, this is 255. More generally, when samples are represented using linear PCM with B bits per sample, MAX is 2B1. For color images with three RGB values per pixel, the definition of PSNR is the same except the MSE is the sum over all squared value differences divided by image size and by three. Alternately, for color images the image is converted to a different color space and PSNR is reported against each channel of that color space, e.g., YCbCr or HSL.

V. Experiments Results

The dataset used in this experiment is from [6], it contains 15 clear images and 8 blurred kernel images. I convolute the 15 clear images with 8 blurred kernel images to get 120 blurred images. The generated 120 blurred images and 15 clear images compose my dataset. All of the preceding methods use this dataset. Some experiment results are shown in Fig. 1, 2, 3. From the visual point of view, HE's method is not good, and the result images by using the last three methods is more clear.

To get a more scientific comparision of experiment results, I use one measure to evaluate these 10 methods on this dataset. For each sharp image, we compute the average PSNR on the blurred images from different kernels and compare among different methods in Fig. 4. The details about this dataset can be found in Fig. 4. From the Fig. 4, the effects of seven methods of image enhancement is not obvious enough, even the PSNR of the processed image is less than the PSNR of the blurred image (for example im09). That is because the histogram equalization is mainly to improve the contrast of the image, so that the intensity is well-distributed. Filtering can filter out the noises, but it will make the image smooth even become blur. This does not prove that the 7 methods are not good, this depends on your research questions and the selections of datasets. So, these 7 methods are not suitable for this dataset. For this dataset, the PSNR of L_0 Sparse Representation inconsistent and take a long time to run. Compare from the evaluation, the values of L_0-Regularized, Dark channel prior are Significantly increased. I note that the L_0 Sparse Representation does not estimate the blur kernel or deblur the image well which also demonstrates the importance of $P_t(x)$ of the proposed prior $P(x)$. However, its program is not packaged, and the parameters are not optimized, resulting in long running time.

Fig. 1. Some experiment results on the dataset by using this ten methods. From Left to Right, Top to Bottom: Blurred image(9th clear image $*$ 3th blur kernel), HE, AHE, CLAHE, Mean flitering, Median flitering, Bilateral filtering, Guassian filtering, L_0 Sparse Representation, L_0-Regularized, Dark channel prior

Fig. 2. Some experiment results on the dataset by using this ten methods. From Left to Right, Top to Bottom: Blurred image(6th clear image $*$ 5th blur kernel), HE, AHE, CLAHE, Mean flitering, Median flitering, Bilateral filtering, Guassian filtering, L_0 Sparse Representation, L_0-Regularized, Dark channel prior

VI. Conclusion

By testing the experiment results, L_0-Regularized and Dark channel prior are better suited to this dataset. In this paper, we can not prove the rest of the methods are bad. Which method is best depends on what problem you are trying to solve. Therefore, for the dataset in this paper, which the main purpose is to remove motion blur, L_0-Regularized and Dark channel prior work better than other methods.

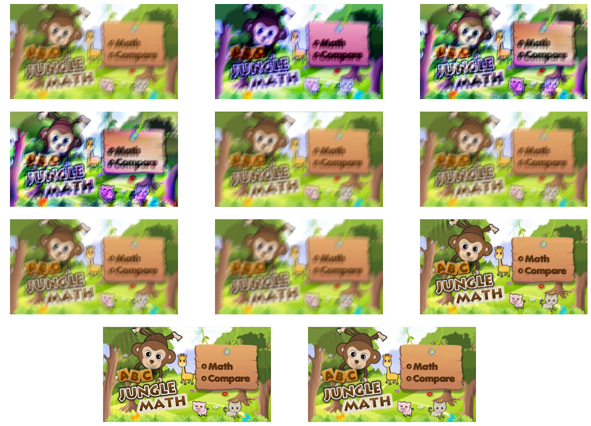

Fig. 3. Some experiment results on the dataset by using this ten methods. From Left to Right, Top to Bottom: Blurred image(15th clear image $*$ 8th blur kernel), HE, AHE, CLAHE, Mean flitering, Median flitering, Bilateral filtering, Guassian filtering, L_0 Sparse Representation, L_0-Regularized, Dark channel prior

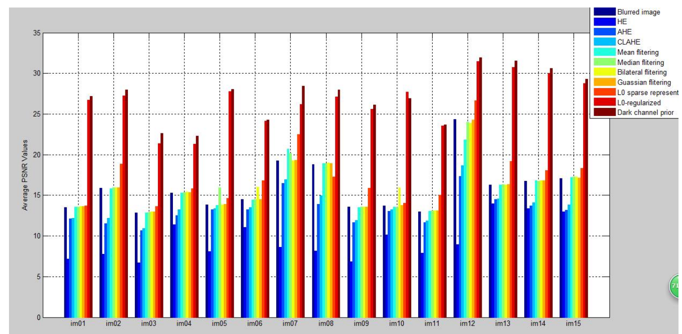

Fig. 4. Quantiatative comparison on the dateset.

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