

PRE-PROCESSING IMAGES USING BRIGHTENING, CLAHE AND RETINEX

Thi Phuoc Hanh Nguyen, Zinan Cai, Mira Park
Centre of Digital Technologies Education Research (CODER)
ICT, School of Technology, Environments & Design
University of Tasmania
mira.park@utas.edu.au

ABSTRACT

This paper focuses on finding the most optimal pre-processing methods considering three common algorithms for image enhancement: Radial brightening, CLAHE and Retinex. The methods are learnt from many different papers with suggested parameters then combine them together to find out the most optimal method for image enhancement for the purpose of image brightening in general. We have carried out the research on the different permutation of three methods Brightening, CLAHE and Retinex. The evaluation is based on Canny Edge detection applied for all processed images then compare the white pixels between images to justify the sharpness.

1. Introduction

Pre-processing nowadays becomes a fundamental step in modern world data storage and transmission including data remote sensing, image database, video coding, etc (Vincent et al. 2009). Pre-processing attracts great attentions from researchers as well as many practical projects in which the pre-processing becomes an integral part for data collection helps to provide high quality of images for analytics. Images are enhanced for biological projects. For instance, the paper named 'Biologically inspired image enhancement based on Retinex' (Wang et al. 2016). The paper illustrates images process method including four steps: illumination estimation, reflection extraction, color-restoration and post-processing. Illumination is based on an available guidance on filter. The reflection step is subject to Retinex algorithm. The paper proposed to use a method named as the modified Contrast–Naturalness–Colorfulness (MCNC) function using the optimal parameters of non-linear stretching to improve the image quality measurement. Other papers 'Observation of deep seafloor by autonomous underwater vehicle' by (Ura 2013) and Enhancement of deep-sea floor images obtained by an underwater vehicle and its evaluation by crab recognition (Ahn et al. 2017) explain the importance of using autonomous underwater vehicles to enhance images quality and highlight some relevant methods used for pre-processing images. The papers raise common issues with undersea images that are the inconsistency between images in different locations and altitudes. A number of methods have been proposed for underwater images to improve the light attenuation, deal with the inconsistency in images quality using homomorphic filtering to remove the effects of non-uniform illumination and some other methods to reduce noises, enhance edges, equal RGB to adjust dominant colours (Ahn et al. 2017). A Retinex-Based Enhancing Approach For Single Underwater Image (Fu et al. 2014) – consider the three most common issues of undersea images of colour distortion, under-exposure and fuzz, the paper proposes a Retinex-based method comprising three steps: colour correction to adjust the distortion in colours, use a variational framework for Retinex to improve brightness and image details. The last step is to improve the reflectance and the illumination by a different strategy.

Through a number of researches, the pre-processing images proves to be analysed mostly for specific area of research which can be marine images, scientific project images, there are not many papers doing research on the

images pre-processing in general or if there exist, those mainly focus on one single pre-processing methods rather than combined many to find the most optimal one.

2. Literature reviews

We have proposed a set of processing steps including the following pre-processing functions:

- Radial Brightening which based on the suggested parameters in a paper by Mehrnejad et al. (2014).
- Contrast Limited Adaptive Histogram Equalization (CLAHE)
- Retinex (Multi Scale Retinex with Colour Restoration and Single-Scale Retinex)

Those methods are separately applied to images and combined with each other to image processing in different sets. Following is the illustration of the each of Brightening, CLAHE and Retinex.

2.1 Radial brightening

The function used in our experiment is based on the recommended algorithm in the research of Mehrnejad et al. (2014). According to which, the value (V_{new}) of an image in HSV is represented based on the value of the point in the middle bottom of the picture (V_{old}) and the distance of a single point in the image towards the middle bottom point (D) as the following:

$$V_{new}(x; y) = V_{old}(x; y) + KD(x; y; x_0; y_0)$$

K in the given equation is chosen as 0.00025 which is chosen through trials according to Mehrnejad et al. (2014). This means that the value of each pixel ($x; y$) in the HSV-based image increases subject to the pixel distance of a particular point to the middle point in the bottom image.

The given single brightening method when applied to the images does not show much difference from the original one.

2.2 Single-Scale Retinex (Parthasarathy et al. 2012) (SCR)

Retinex algorithm, in mathematics is represented as:

$$R(x; y) = \log(I(x; y)) - \log[F(x; y) * I(x; y)]$$

convolution operation. $R(x, y)$ is the associated Retinex output. $F(x, y)$ is a Gaussian surround function which is represented as

$$F(x, y) = e^{-r^2/c^2}$$

For the Gaussian function, c is the dynamic range compression which is sacrificed to improve the rendition. It means that we cannot achieve $F(x, y)$ and c of high value at a time. This is a drawback of Single-Scale Retinex and multiple scale Retinex is born to deal with that (Jobson et al. 1997)

2.2.1 Multi scale Retinex with Colour restoration (MSCR)

According to Jobson et al. (1997), Retinex algorithm makes images to be ‘greying out’ which means that all three bands of an image are the same after the processing and turns the images into a desaturated image which can be severe in many cases. The proposed restoration algorithm in that paper suggests the function to avoid the side effect of Retinex.

The algorithm for colour restoration is given below:

$$R(MSRCR_i)(x, y) = G(C_i(x, y)R(MSR_i)(x, y) + b$$

Where $C_i(x, y) = f[C_i(x, y)]$ is the i^{th} band of the colour restoration function(CRF) and $RMSRCR_i$ is the i^{th} spectral band of the multiscale retinex with colour restoration.

$$C_i(x, y) = \beta \log[\alpha I'_i(x, y)] = \beta \log[\alpha I_i(x, y)] - \beta \log\left[\sum_{i=1}^S I_i(x, y)\right]$$

where β is a gain constant, α controls the strength of the non-linearity, G and b are final gain and offset values. The values specified for these constants suggested in the paper (Jobson et al. (1997)) are $\beta = 46$, $\alpha = 125$, $b = -30$, $G = 192$. On implementation this algorithm, we utilise the suggested parameters from this paper.

This algorithm helps to enhance images by using a wide range of nonlinear illumination conditions. The algorithm uses different parameters subject to the consideration on different kinds of images. Based on a research by Parthasarathy et al. (2012), which illustrates the instructions to find out proper parameters automatically. The paper also admits the failure of the Multi Scale Retinex with Colour Restoration as it still results in greyed out images.

2.3 Contrast Limited Adaptive Histogram Equalization (CLAHE)

CLAHE has been widely used for image enhancement on a histogram basis (Reza 2004). To be more specific, the algorithm is originated from the assumption that the consistency in all areas within an image is maintained. And all those areas on the image will be enhanced by one unique grayscale mapping. However, when moving from different areas in an image, the distribution of grayscales varies which means there needs to have a method to equalize the image grayscale distribution. Adaptive histogram equalization method supports the finding of the mapping for each pixel subject to its neighbour population of grayscale. As each pixel gets the calculation of contrast enhancement mapping, the number of that method repeated is the number of pixels in an image which means that this method requires an extensive computational basis (Reza 2004).

Technically, CLAHE does this by setting a threshold. If some grey level in the image exceed the threshold, the excess is evenly distributed to all grey levels. After this processing, the image will not be over-enhanced, and the problem of noise amplification can be reduced (Pier 1987)

For the blocky area problem of Adaptive Histogram Equalization, this paper proposes an interpolation algorithm. By increasing the number of mapping function values of each pixel to balance the differences in gray values of adjacent local image processing blocks. Excluding the edge part of the image, most pixels in the image will use the nearest 4 processing windows to calculate the mapping function, avoiding the generation of discontinuous block images.

OpenCV provides the CLAHE function. This function takes two parameters, clipLimit and tileGridSize. clipLimit represents the threshold clip size mentioned above. tileGridSize represents the size of the image processing window.

After applying three functions of pre-processing in different ways, Canny Edge detection is utilised to evaluate the edge detection extent of different set of applied method. Canny Edge detection algorithm represents a two-direction spatial measurement in images. Canny Edge edge detector uses two 3x3 convolution masks with x-direction and y-direction illustrate estimating gradient. Canny Edge detection is said to be highly sensitive with noises and highly recommended for data communication and data transfer (Vincent et al. 2009), this is also the reason why we opt for Canny Edge detection for image evaluation to effectively highlight noises as edges as it was found

3. Methods

3.1 Using Canny Edge detection on processed images and white pixel calculation

Given the three algorithms mentioned before, we combine different sets of algorithms on the image sample including 15 following combinations: Retinex, CLAHE, Brightening, Retinex – CLAHE, CLAHE – Retinex, CLAHE – Brightening, Brightening – CLAHE, Retinex – Brightening, Brightening – Retinex, Brightening – CLAHE – Retinex, Brightening – Retinex – CLAHE, CLAHE – Retinex – Brightening, CLAHE – Brightening – Retinex, Retinex – CLAHE – Brightening, Retinex - Brightening - CLAHE. The processed images then be cropped in starfish images. With cropped images, we use boundingRect operation to create mask to reduce noises while highlight edges of objects within images. Methods of pre-processing are applied on 15 images ranging from Image 0 to Image 14. Starfish images are only found on Image 0, Image 1, Image 5, Image 7, Image 9.

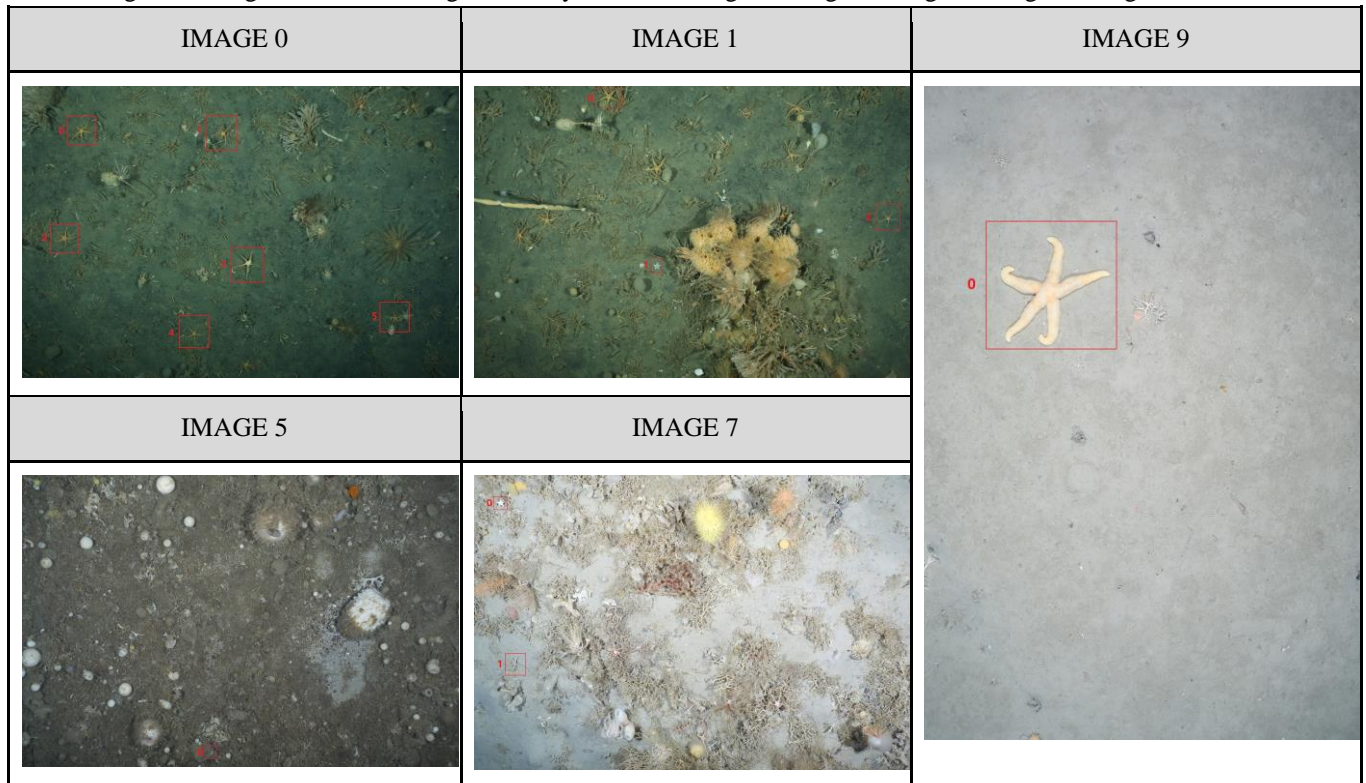


Figure 1: Starfish crops from image 0, image 1, image 5, image 7, image 9 in red squares.

After applying these sets on the image separately, we use Canny Edge detection

We have applied above mentioned 15 sets of pre-processing on the 15 samples, then apply Canny Edge detection as an edge detector tool with edges represented by white lines, where has a sharp change in intensity and where has a sharp change in colour.

We have a number of cropped images of starfish getting from the processed images, then use the boundingRect, which is an OpenCV image editing component, creating a mask to eliminate the noises around starfish object itself then calculate the white pixel of object images.

Following is the images processing procedure summarised into a diagram:

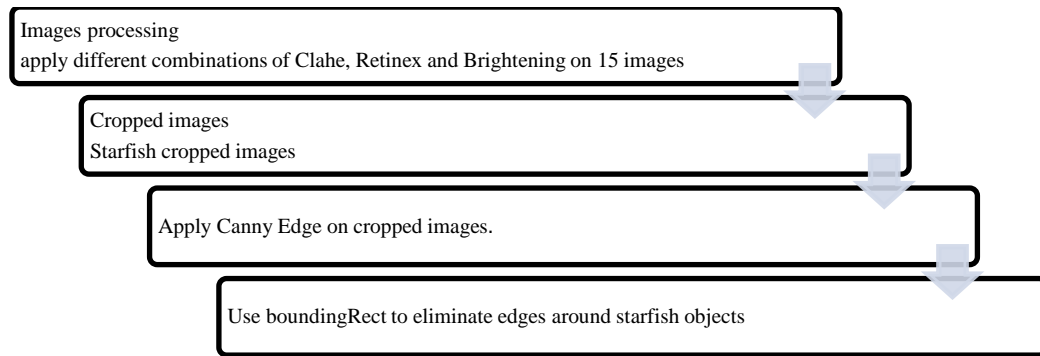


Figure 2: Pre-processing procedure

The code of program has been uploaded to GitHub for further research as link below.

[LINK](#)

4. Results

The appendix A illustrates the cropped processed images after applying Canny Edge detection on. Following is the Figure 2 which is the white pixel calculation of those crops after above-mentioned four steps in the Figure 1. Of all 13 cropped images, there are 06 pre-processed images with CLAHE have the biggest number of white pixels, 04 images get the most white pixel when applying Brightening and CLAHE and 03 images get the most white pixel after CLAHE and Brightening pre-processing. This proves that those pre-processing sets that include CLAHE, in general, are most effective in adjusting the sharpness of images.

When compare the brightening images with originals, the white pixel increases slightly which is as the same result when compare the Retinex-Brightening and the Retinex only, the difference between the two is minor. The Brightening pre-processing, in conclusion, shows little effect on image sharpness enhancement.

Retinex: The Retinex does not help much in increasing the sharpness. Each methods combination with Retinex will significantly reduce the number of white pixels. In corporation with Retinex, the Brightening even reduces the sharpness of images showing by the white pixel of Retinex images ranging from 400 to around 200 all fall down to almost 0. The single Retinex images are all of low white pixels compare to the images processed by other methods.

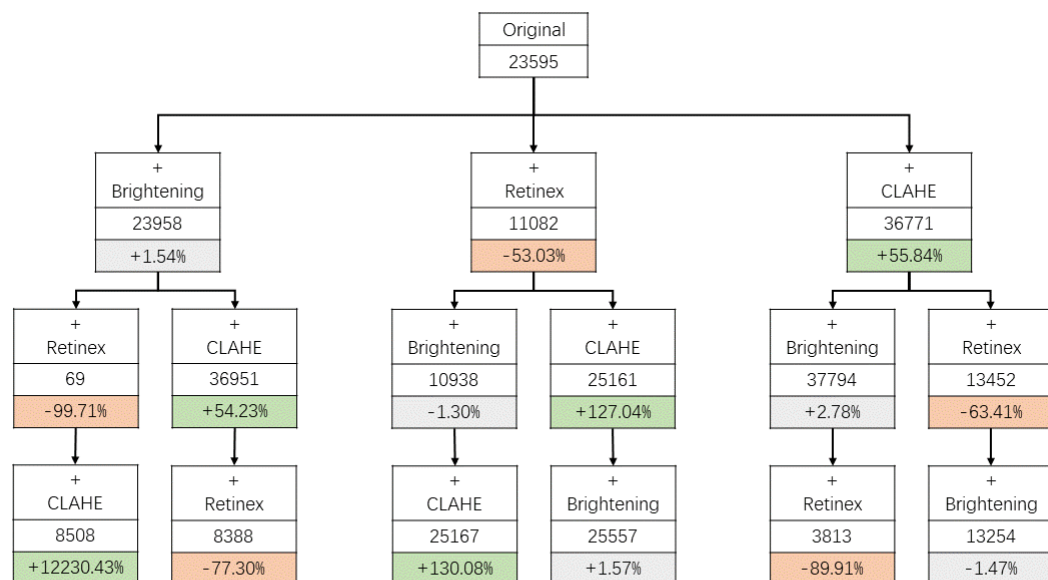
Order of pre-processing methods within a combination make differences in defining white pixel, for example, when apply Brightening then Retinex on an image, the white pixel counted is different from applying Brightening after Retinex or the different orders within Brightening, Retinex, CLAHE result in difference in white pixel numbers.

	Witho ut pre- procssi ng	Brighteni ng	Retine x	CLAH E	Brighteni ng + Retinex	Retinex + Brighten ing	Brightenin g + CLAHE	CLAHE + Brighte ning	Retinex + CLAHE	CLAHE + Retinex	Brighte ning + Retinex + CLAHE	Brighte ning + CLAHE + Retinex	Retinex + Brighte ning + CLAHE	Retinex + CLAHE + Brighte ning	CLAHE + Brighte ning + Retinex	CLAHE + Retinex + Brighte ning
IMAGE 0																
i0_crop_0	1893	2037	552	2532	0	516	2517	2433	2019	900	198	492	2112	2016	0	921
i0_crop_1	2067	2127	1917	2142	0	1764	2094	2139	2130	1590	1530	1188	2133	2124	657	1569
i0_crop_2	2208	2241	864	2670	0	858	2643	2649	2298	1194	498	591	2238	2322	0	1275
i0_crop_3	3768	3828	2790	3966	0	2973	4053	4014	3780	2961	2544	2325	3696	3720	1599	2940
i0_crop_4	2367	2388	2118	2877	0	2151	2838	2844	2589	1986	1665	1497	2526	2670	738	2010
i0_crop_5	1662	1737	789	1842	0	738	1917	1851	1626	753	504	519	1602	1602	48	672
IMAGE 1																
i1_crop_0	1863	1905	933	2142	0	801	2067	2127	1842	966	633	831	1884	1899	300	954
i1_crop_1	483	537	219	681	0	288	771	744	513	297	162	210	558	543	93	258
i1_crop_2	1644	1779	291	2103	0	252	2139	2151	1779	423	96	297	1800	1854	0	408
IMAGE 5																
i5_crop_0	1290	1233	1305	1554	0	1239	1467	1509	1425	951	1161	411	1434	1383	354	1065
IMAGE 7																
i7_crop_0	576	495	138	645	69	138	750	675	615	312	204	225	573	624	159	279
i7_crop_1	1362	1383	471	1845	0	459	1674	1854	1305	561	474	213	1347	1323	219	606
IMAGE 9																
i9_crop_0	3702	3501	0	13326	0	0	13488	14313	4665	1509	0	0	4698	4860	0	1362

Figure 3: Calculation of true positive pixel of different pre-processed cropped images after applying Canny Edge detection.

In the evaluation of the role of radial brightening, CLAHE and Retinex based on Canny Edge detection and pixels calculation, we have come up with the following conclusions: Firstly, CLAHE, CLAHE-Brightening and Brightening-CLAHE prove to be the most effective methods in defining the sharpness of process images.

In most of the cases, the single CLAHE proves to be the most helpful tool for edge defining. Those methods are simple and easy to use without much requirements on computational basis and the function of CLAHE is available to use as it is provided by OpenCV library. Secondly, the radial brightening does not show much effect on image enhancement using the suggested parameter by Mehrnejad et al. 2014. A more extensive research after this paper should focus on trying different parameters for radial brightening method. Lastly, the Retinex still cannot improve image quality as it reduces the sharpness with the minimum number of white pixels in an image. **Due to a limited scope of the research, the training model has not been implemented for evaluation purpose, therefore, this paper can only emphasise on the pixel calculation of Canny Edge detection images to evaluate the whole images' sharpness which might not be highly precise to the object extent. The image histogram method has shown the consistent result with the Canny Edge detection with pixel calculation. They all claim that CLAHE and the combination of CLAHE and Brightening are the most effective compared to other given methods. With more time available, the paper should expose more parameters on each method.**



Note:

Methods of pre-processing
Total number of true positive Pixel counted
The increase/ decrease compared to the previous pre-processing image in previous step.

Figure 3: Sum of white pixel calculation of all pre-processed cropped images by each step.

According to **Figure 2**, the table can be converted to the flow chart as Figure 3. The second row of the chart corresponds to the single preprocessing method. The second row represents the combination of two images preprocessing functions using. And the data of the last row can represent the effect of all preprocessing using together in different sequences. The first row of single chart is the method of preprocessing. The second row is

the sum of white pixels in all sample images. Compared to the previous process, the percentage change in the number of white pixels will be shown in the third row.

From the flow chart, we can find that after implement Retinex method, all the number of the white pixel have a significant decrease from -53.03% to -99.71%. All the number after using CLAHE increase from 54.23% to 12230.43%. With the brightening method, the number does not change a lot (+2.78% to -1.47%), which can be considered as almost no change at all.

In conclusion, the CLAHE function can significantly increase the effect of canny edge detection. In contrast, Retinex method would seriously affect the result of edge detection. And the brightening process may not change the result a lot.













































































































5. Discussions













































































































First, the entire project analyzed only 13 starfish in 5 pictures. Future research should use a large number of images datasets to ensure credibility. Secondly, this project uses boundingRect, an OpenCV image editing component, to manually create a starfish mask. But for datasets with a large number of pictures, this method is very time-consuming. Therefore, we should explore whether there is an automated way to create a mask. Finally, for the average 13-megapixel image used in this project, the Brightening method takes 40 seconds, and the Retinex algorithm takes 3 minutes. Therefore, if a subsequent use of a dataset containing a large number of pictures, a high-performance processor may be necessary.

6. Reference

- [1] Fu, X. Zhuang, P. Huang Y. Liao, Y. Zhang, X. P., & Ding, X. 2014, 'A retinex-based enhancing approach for single underwater image', *2014 IEEE International Conference on Image Processing (ICIP)* (pp. 4572-4576), IEEE.
- [2] Ibrahim, H. and Pik Kong, N. 2007, 'Brightness Preserving Dynamic Histogram Equalization for Image Contrast Enhancement', *IEEE Transactions on Consumer Electronics*, no. 53(4), pp.1752-1758.
- [3] Jobson, D.J. Rahman, Z.U. and Woodell, G.A. 1997, 'A multiscale retinex for bridging the gap between colour images and the human observation of scenes'. *IEEE Transactions on Image processing*, no. 6, pp. 965-976.
- [4] Ketcham, D.J., Lowe, R.W. and Weber, J.W., 1974, 'Image enhancement techniques for cockpit displays', *Hughes Aircraft Co Culver City Ca Display Systems Lab*.
- [5] Mehrnejad, M. Albu, A. Capson, D. and Hoeberechts, M. 2014, 'Towards robust identification of slow moving animals in deep-sea imagery by integrating shape and appearance cues', *ICPR Workshop on Computer Vision for Analysis of Underwater Imagery*, pp. 25-32, IEEE.
- [6] Parthasarathy, S. Sankaran, P. 2012, 'An automated multi scale retinex with colour restoration for image enhancement'. *National Conference on Communications (NCC)* (pp. 1-5), IEEE.
- [7] Pizer, S. M., Amburn, E. P., Austin, J. D., Cromartie, R., Geselowitz, A., Greer, T. Zuiderveld, K. 1987, 'Adaptive histogram equalization and its variations', *Computer vision, graphics, and image processing*, no. 39(3), pp. 355-368.
- [8] Reza, A. M. 2004, 'Realization of the contrast limited adaptive histogram equalization (CLAHE) for real-time image enhancement', *Journal of VLSI signal processing systems for signal, image and video technology*, no. 38(1), pp. 35-44.
- [9] Vincent, O. R., & Folorunso, O. 2009, 'A descriptive algorithm for Canny Edge image edge detection', In *Proceedings of Informing Science & IT Education Conference (InSITE)*, Vol. 40, pp. 97-107). California: Informing Science Institute.
- [10] Wang, Y., Wang, H., Yin, C., & Dai, M. 2016, 'Biologically inspired image enhancement based on Retinex', *Neurocomputing*, no. 177, pp. 373-384.
- [11] Zuiderveld, K., 1994, 'Contrast limited adaptive histogram equalization', In *Graphics gems IV*, pp. 474-485, Academic Press Professional, Inc.

Appendix A:

	Original image	Without pre-processing	Ground Truth	Brightening	Retinex	CLAHE	Brightening + Retinex	Retinex + Brightening	Brightening + CLAHE	CLAHE + Brightening	Retinex + CLAHE	CLAHE + Retinex	Brightening + Retinex + CLAHE	Brightening + CLAHE + Retinex	Retinex + Brightening + CLAHE	Retinex + CLAHE + Brightening	CLAHE + Brightening + Retinex	CLAHE + Retinex + Brightening
IMAGE 0																		
i0_crop_0		1893		2037	552	2532	0	516	2517	2433	2019	900	198	492	2112	2016	0	921
																		
i0_crop_1		2067		2127	1917	2142	0	1764	2094	2139	2130	1590	1530	1188	2133	2124	657	1569
																		
i0_crop_2		2208		2241	864	2670	0	858	2643	2649	2298	1194	498	591	2238	2322	0	1275
																		
i0_crop_3		3768		3828	2790	3966	0	2973	4053	4014	3780	2961	2544	2325	3696	3720	1599	2940
																		
i0_crop_4		2367		2388	2118	2877	0	2151	2838	2844	2589	1986	1665	1497	2526	2670	738	2010
																		
i0_crop_5		1662		1737	789	1842	0	738	1917	1851	1626	753	504	519	1602	1602	48	672
																		

	Original image	Without pre-processing	Ground Truth	Brightening	Retinex	CLAHE	Brightening + Retinex	Retinex + Brightening	Brightening + CLAHE	CLAHE + Brightening	Retinex + CLAHE	CLAHE + Retinex	Brightening + Retinex + CLAHE	Brightening + CLAHE + Retinex	Retinex + Brightening + CLAHE	Retinex + CLAHE + Brightening	CLAHE + Brightening + Retinex	CLAHE + Retinex + Brightening
IMAGE 1																		
i1_crop_0		1863		1905	933	2142	0	801	2067	2127	1842	966	633	831	1884	1899	300	954
																		
i1_crop_1		483		537	219	681	0	288	771	744	513	297	162	210	558	543	93	258
																		
i1_crop_2		1644		1779	291	2103	0	252	2139	2151	1779	423	96	297	1800	1854	0	408
																		
IMAGE 5																		
i5_crop_0		1290		1233	1305	1554	0	1239	1467	1509	1425	951	1161	411	1434	1383	354	1065
																		
IMAGE 7																		
i7_crop_0		576		495	138	645	69	138	750	675	615	312	204	225	573	624	159	279
																		
i7_crop_1		1362		1383	471	1845	0	459	1674	1854	1305	561	474	213	1347	1323	219	606
																		
IMAGE 9																		
i9_crop_0		3702		3501	0	13326	0	0	13488	14313	4665	1509	0	0	4698	4860	0	1362
	