



Visual Improvements in Color Image Processing Using Regularized Filtration

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Abstract: This paper proposes a generic filtering approach to filter the various kinds of artefacts created by Radiometric or color modifications. This approach uses streaming map regularization along histogram equalization to perform the color and contrast enhancement of an image. The streaming map is defined as a difference between the original and the corrected image. The proposed method relies on the nonlocal Yaroslavsky filter to regularize the streaming map. In this paper, Adaptive Histogram equalization, jpeg compression and decompression techniques are applied on digital image which leads to some visual artefacts. Then Streaming map which is the difference between original image and transformed image is calculated, then a generic filtering method also called (Recursive regularized filter) RRF filter which draws on the nonlocal Yaroslavsky filter is used to regularize the streaming map so that artefacts are suppressed. The performance of this method is evaluated through measures such as MSE, PSNR and Variance. Performance measures such as MSE, PSNR and Variance are calculated over Transformed image and RRF Filtered image and compared.

Keywords: Image enhancement, Histogram equalization, RRF filter.

I. Introduction

The principal objective of image enhancement [1] is to process a given image so that the result is more suitable than the original image for a specific application. The color and contrast modifications [2] are elementary tools for image enhancement. Such changes may be obtained by applying a prescribed function to the gray values of images, as in contrast stretching or Gamma correction, or by prescribing the histogram [7] of the resulting image, as in histogram equalization [8], [9] or specification. These techniques extend to color images by considering a luminance channel, as in Gamma correction, or by working on each color channel separately.

Image compression is minimizing the size in bytes of a graphics file without degrading the quality of the image to an unacceptable level. The reduction in file size allows more images to be stored in a given amount of disk or memory space. It also reduces the time required for images to be sent over the Internet or downloaded from Web pages. Image compression can be achieved by compression techniques such as GIF, PNG, JPEG and Progressive JPEG.

The drawback of color and contrast modification techniques and compression techniques is to create visual artifacts such as noise enhancement, detail loss, texture washing, color proportion inconsistencies [11] and compression artifacts [12], [13]. Several methods have been proposed in last few years to remove artifacts from color and contrast modification. The simplest one is proposed in [18] in the context of local histogram modifications and amounts to limit the modification depending on gradient values. While improving the results in some cases, this approach let most artifacts untouched. In [5], it is proposed to correct color transfer artifacts by using variation regularization after the transfer. Still in a variation framework, the authors of [10] propose a unified formulation containing both color transfer and regularity constraints in a single energy minimization. For the problem of color proportion, a possible approach is to transfer color after having identified some homogeneous regions, as proposed in [6] and [19]. A related class of works takes interest in the avoidance of compression artifacts, usually using the properties of the compression scheme [20].

This paper proposes universal filtering called streaming map regularization (RRF) filtering technique to remove the compression artifacts. The streaming map defined as the image of the differences between the original image and the one after contrast or color modification. In order to regularize this map without introducing blur in the final image, the proposed approach take inspiration from nonlocal methods that have been proposed for image denoising and more precisely from the Yaroslavsky filter [21]. The streaming map is filtered by averaging pixel values using weights that are computed on the original image, therefore adapting to the geometry of this initial image. The complete artifacts are getting suppressed by iterating this filtering stage progressively Performance measures such MSE, PSNR and Variance are calculated over transformed images and filtered images and

compared those results separately for two transformed images. RRF filter gives better results compared to mean, median and wiener filters.

The remainder of the paper is organized as follows: section II gives the details about the histogram equalization and adaptive histogram equalization methods. Section III gives the details about the proposed RRF filter. The experimental results are provided in section IV and finally conclusions are given in section V.

II. ADAPTIVE HISTOGRAM EQUALIZATION (AHE) [18]

The input image is preprocessed that is color image is separated into three planes and size will be changed to 256x256 image. Adaptive histogram equalization method is used to change contrast of an input image. Adaptive Histogram Equalization [14] method is an extension to traditional Histogram Equalization technique. It enhances the contrast of images by transforming the values in the intensity image. Unlike histogram equalization, 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 matches 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. The transformation of an image can be using AHE after preprocessing. The main steps of the methodology for removal of artefacts are the following: read the input image, preprocessing of image, transformation of image, filtering of image by different methods, comparing performance measures for all filter outputs.

The block diagrams for removing artefacts from AHE image and AHE plus JPEG Encoding [15] and Decoding image using mean filter are shown in Fig 1 and Fig 2. In Fig 1, the input image is preprocessed that is color image divided into three planes, and then Adaptive Histogram Equalization method is applied to change the contrast. Visual artefacts such as Noise enhancement, detail loss, color proportion inconsistencies are introduced. Mean filtering is applied to remove those artefacts and performance measures such as MSE, PSNR and Variance are calculated. In Fig 2, the input image is preprocessed that is color image divided into three planes, then Adaptive Histogram Equalization method is applied to change the contrast and then JPEG Encoding & Decoding Technique is applied for compressing and decompressing. Visual artefacts such as Noise enhancement, detail loss, color proportion inconsistencies, compression artefacts are introduced. Mean filtering is applied to remove those artefacts and performance measures such as MSE, PSNR and Variance are calculated.

Fig.1. Block diagram for removing artifacts using AHE using mean/ median filter

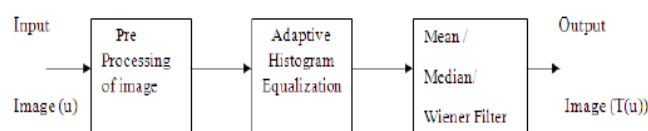
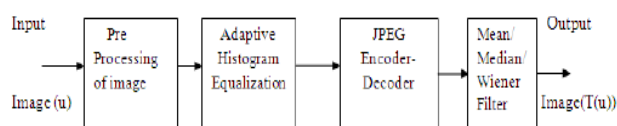


Fig.2. Block diagram for removing artifacts using AHE plus JPEG coding using mean/median filter



The block diagrams for removing artefacts from AHE image and AHE plus JPEG Encoding and Decoding image using RRF filter are shown in Fig 3 and Fig 4. In Fig 3, the input image is preprocessed that is color image divided into three planes, and then Adaptive Histogram Equalization method is applied to change the contrast. Visual artefacts such as Noise enhancement, detail loss, color proportion inconsistencies are introduced. RRF filtering is applied to remove those artefacts and performance measures such as MSE, PSNR and Variance are calculated. In Fig 4, the input image is preprocessed that is color image divided into three planes, then Adaptive Histogram Equalization method is applied to change the contrast and then JPEG Encoding & Decoding Technique is applied for compressing and decompressing. Visual artefacts such as Noise enhancement, detail loss, color proportion inconsistencies, compression artefacts are introduced. RRF filtering is applied to remove those artefacts and performance measures such as MSE, PSNR and Variance are calculated.

Fig 3. Block diagram for removing artefacts from AHE image using RRF filter

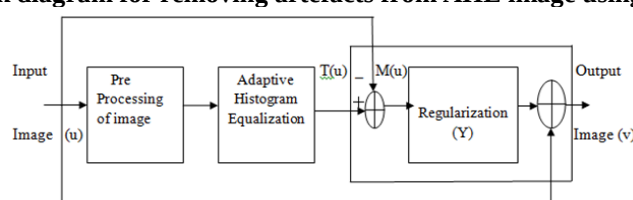
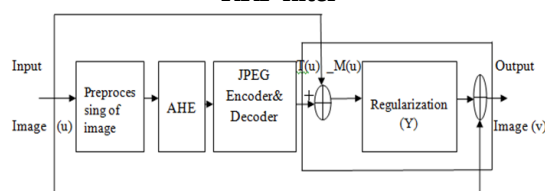


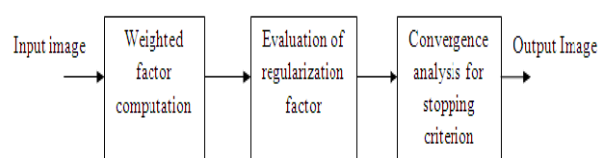
Fig 4: Block diagram for removing artefacts from AHE plus JPEG Encoding& Decoding image using RRF filter



III. RECURSIVE REGULARIZED FILTER (RRF)

The block diagram for RRF Filter is shown in Fig 5. The streaming map $M(u)$ which is the difference between transformed image and original image is applied to RRF Filter. In this, weighted factor is computed, Regularization term is evaluated, finally stopping criterion is found out regularization process convergence. Then enhanced image will be obtained by combining the regularized image with original image (u).

Fig 5: Block diagram of RRF Filter



All the artefacts mentioned above are removed by regularizing the *streaming map*, which is defined as the image of the differences between the original image and the one after contrast or color modification. All these artefacts may be interpreted as spatial irregularities of this streaming map. In order to regularize this map without introducing blur in the final image, inspiration is taken from nonlocal methods that have been proposed for image denoising and more precisely from the Yaroslavsky filter. The streaming map is filtered by averaging pixel values using weights that are computed on the original image, therefore adapting to the geometry of this initial image. It will be shown that artefacts are progressively suppressed by iterating this filtering stage.

$T(u)$ is the image after color or contrast modification. In what follows, we write $M(u) := T(u) - u$ for the streaming map of image. We propose to regularize it thanks to the operator Y_u , a weighted average with weights depending on the similarity of pixels in the original image. The effect of this operator on an image $v: \Omega \rightarrow \mathbb{R}$ with $n \geq 1$ which is defined as;

$$Y_u(v): X \in \Omega \rightarrow \frac{1}{c(x)} \int_{y \in N(x)} v(y) \cdot w_u(x, y) dy$$

With weights $w_x(x, y) = \frac{\|u(x) - u(y)\|^2}{\sigma^2}$

We calculate the streaming map which gives the difference between original image and transformed one. Y_u is the operator, a weighted average with weights depending on the similarity of pixels in the original image u . We calculate the weights for each and every pixel leaving the first pixel; we start from second pixel. we take 8 neighbor hoods of each pixel. Where $\|\cdot\|$ stands for the Euclidean distance in $\mathbb{R}_n$, where,

$$N(x) = x + N(0) \subset \Omega$$

with $N(0)$ a spatial neighborhood of 0, where σ is a tuning parameter $C(x)$ of the method and is the normalization constant.

$$c(x) = \int_{y \in N(x)} w_u(x, y) dy$$

We will add all the weights which are calculated for each and every pixel. Observe that if we apply to the image u , we obtain the Yaroslavsky filter. If the weights also decrease as a function of the distance to x , Y_u becomes similar to the cross bilateral filter introduced in [19] for flash photographic enhancement. The regularization of the image $T(u)$, referred to as streaming map regularization (RRF), is then defined as;

$$RRF_u(T(u)) := u + Y_u M(u).$$

Now, observe that this formulation can be divided in two terms as of image;

$$RRF_u(T(u)) = Y_u(T(u)) + u - Y_u(u).$$

First, the image $T(u)$ is filtered by a nonlocal operator Y_u , following the regularity of the image. This operation attenuates noise, compression, and color proportion artefacts but also the details of the image $T(u)$. The second operation performed by the RRF filter consists in adding the quantity,

$$u_{\text{details}} := u - Y_u(u),$$

which can be considered as details of the original image (e.g., texture and fine structures). The previously defined filter has several nice properties which enable us to reduce the visual artefacts. First, observe that this filter leaves all the images, $u + \lambda$, $\lambda \in \mathbb{R}_n$, unchanged. Moreover, if the application consists of a multiplication by a positive constant α , then α .

$$\text{RRF}_u(\alpha u) = \alpha u + (1 - \alpha).$$

If $\alpha > 1$, the transfer increases the contrast. In that case, the RRF filter reduces the noise contained in the image difference. If $\alpha < 1$ the transfer decreases the contrast and the RRF filter restores the lost details contained in u . Finally, another interesting aspect of the RRF filter is that the discrete distribution of the regularized image $\text{RRF}_u(T(u))$. This property somewhat prevents the creation of false colors which may be caused by the regularization process. In practice, more than one iteration of the RRF filter is required to remove all the aforementioned artefacts. The image $T(u)$ after k iterations of the RRF filter can be written as follows,

$$\text{RRF}_u^k(T(u)) = Y_u^k(T(u) - u) - u$$

There Y_u^k refers to the recursive use of the Y_u filter. The question is then how to choose the right number of iterations k and one may wonder what happens for large values. Studying the limit Y_u^k of when $k \rightarrow \infty$ boils down to the study of the limit of the powers of a matrix. Indeed, let us resize the discrete image into a column vector v of size m . In this setting, the linear filter Y_u can be written as an matrix, whose coefficients are;

$$A_{i,j} = \frac{w_u(i,j)|_{j=N(i)}}{\sum_{k=1}^m w_u(i,k)|_{k=N(i)}}, \quad 1 \leq i,j \leq m.$$

In this formulation, i is the index in the vector v of a pixel x in u , and $N(i)$ is the set of indexes in corresponding to the 2-D neighborhood $N(x)$ in u . If we resize the map $T(u)-u$ into the vector w , then $Y_u^k(T(u) - u)$ corresponds to the vector $A^k w$. Now, observe that the matrix A is stochastic,

$$\text{i.e., that } A_{i,j} \geq 0, \text{ and } \sum_{j=1}^m A_{i,j} = 1.$$

If we assume that A is primitive, i.e., that is strictly positive for some $r \in \mathbb{N}^*$ and this is clearly true if the neighborhoods $N(x)$ are disks of radius $\rho > 1$ in u , the Perron-Frobenius theorem permits to conclude that A^k tends toward a stochastic matrix A_∞ when $k \rightarrow +\infty$, and that all of the lines of A_∞ are equal. This means that the map $Y_u^k(T(u) - u)$ tends toward a constant image $Y_u^\infty(T(u) - u)$. In other words, the limit image is only a shift of the image u by a constant color. The Perron-Frobenius theorem also gives information on the convergence rate A_∞ of towards A_∞ .

More precisely, we know that $A^k - A_\infty$ behaves as $O(\lambda^r r^{m(\lambda)-1})$, where λ is the Eigen value of A with the second largest modulus and where $m(\lambda)$ is the algebraic multiplicity of λ . In practice $\|\lambda\|$, is generally close to 1 for a similarity matrix A , and the resulting convergence rate is quite slow. In order to control the iterations of the RRF filter, we compute at each iteration a convergence map, written and defined at each pixel as follows:

$$c(x) = \|Y_u^k(M(u(x)) - Y_u^{k-1}(M(u(x)))\|$$

Where $\|\cdot\|$ is the average Euclidean norm in $\mathbb{R}_n$. We then consider that there is numerical convergence in pixel x when, $C(x) < t$ and the RRF filter is only applied to pixels for which the convergence map is greater than the threshold t . In all experiments, the convergence threshold has been set equal to $t = 1$ (for $n^* 8$ -bit images). In practice, if x is the first pixel to attain this numerical convergence, this boils down to replace the line corresponding to x in matrix A by the same line in the identity matrix. The new matrix is A_1 then iterated until a second pixel attains numerical convergence, and is then replaced by A_2 , etc. Observe that each matrix A_j is stochastic and such that converges when $k \rightarrow +\infty$, which implies that a new pixel attains numerical convergence after a finite number k_j of iterations. The whole process hence stops once all pixels satisfy $C(x) < t$. At the end, if v is the vector corresponding to $T(u)-u$, we get $v^\infty = A_{n-1}^{k_{n-1}}, \dots, A_1^{k_1}, A_0^{k_0}$. Observe that the proposed stopping criterion permits also to save computation time since the iterations of the RRF filter concern fewer and fewer pixels.

IV. RESULTS

This section gives the details about the proposed approach. It also gives the results of the histogram equalization and adaptive histogram equalization also for the purpose of comparison. To evaluate the performance in this PSNR and MSE are evaluated and they are checked with earlier approaches. The measuring parameters are defined as :

1. Mean squared error: The Mean squared error (MSE) of an estimator is one of the way to quantify the amount by which an estimator differs from the true value of the quantity being estimated. As a loss function, MSE is called squared error loss. MSE measures the average of the square of the error. The error is the amount by which the estimator differs from the quantity to be estimated;

$$MSE = \frac{1}{M \times N} \sum (f - \hat{f})^2$$

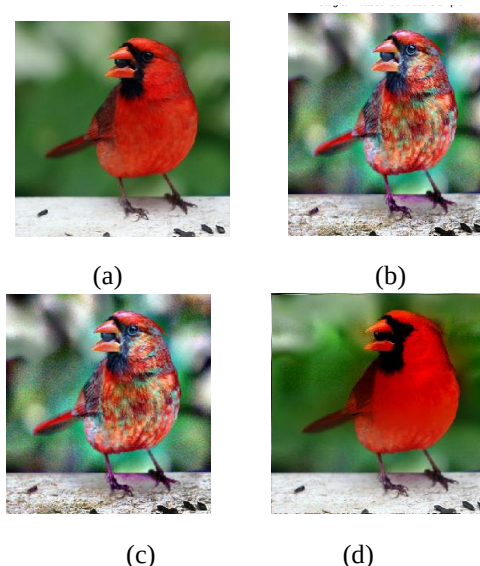
Where f is the original image and $\hat{f}$ is the recovered image after Decoding.

2. PSNR : The PSNR is most commonly used as a measure of quality of reconstructed image .Peak signal-to-noise ratio, defined as a ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. PSNR is usually expressed in terms of the logarithmic decibel scale.

$$PSNR(dB) = 10 \log_{10} \left(\frac{I_{peak}^2}{MSE} \right)$$

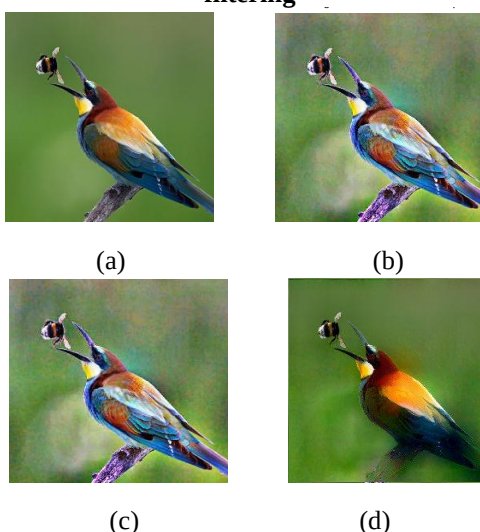
Where I_{peak} is the peak values of the input signal.

Fig.5. a) Original image b) Image after AHE c) image after AHE plus JPEG coding d) image after RRF filtering



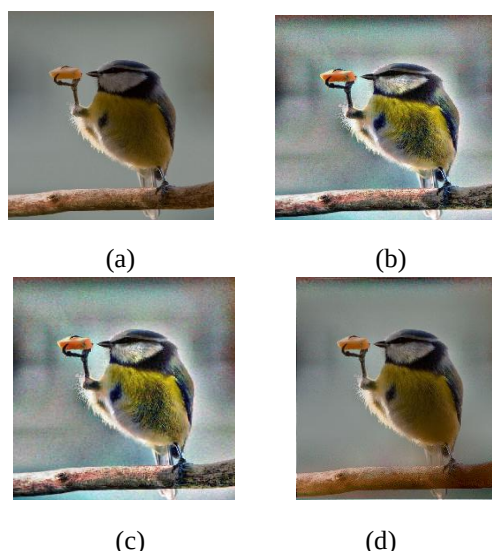
Error Index matching for Histogram-JPEG coding =2828.5124
 Error Index matching for RRF-JPEG coding =854.4205
 PSNR for Histogram-JPEG coding =31.3502
 PSNR for RRF-JPEG coding =43.321

Fig.6. a) Original image b) Image after AHE c) image after AHE plus JPEG coding d) image after RRF filtering



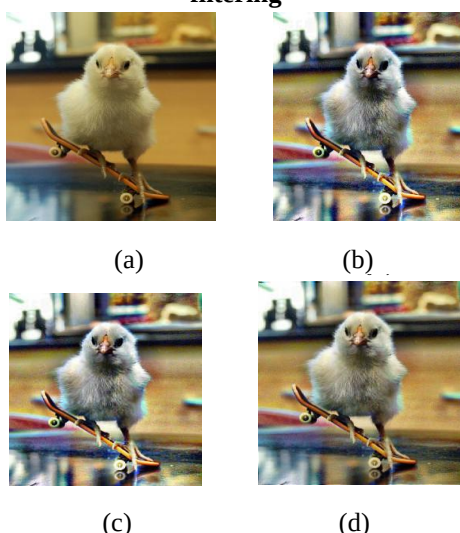
Error Index matching for Histogram-JPEG coding =1067.3816
 Error Index matching for RRF-JPEG coding =736.8711
 PSNR for Histogram-JPEG coding =41.0956
 PSNR for RRF-JPEG coding =44.8011

Fig.7. a) Original image b) Image after AHE c) image after AHE plus JPEG coding d) image after RRF filtering



Error Index matching for Histogram-JPEG coding =1294.8835
 Error Index matching for RRF-JPEG coding =240.6446
 PSNR for Histogram-JPEG coding =39.1635
 PSNR for RRF-JPEG coding =55.9921

Fig.8. a) Original image b) Image after AHE c) image after AHE plus JPEG coding d) image after RRF filtering



Error Index matching for Histogram-JPEG coding =2087.9287
 Error Index matching for RRF-JPEG coding =798.4254
 PSNR for Histogram-JPEG coding =34.386
 PSNR for RRF-JPEG coding =43.9989

V. CONCLUSIONS

In this paper a generic filtering procedure is used in order to remove the different kinds of artefacts created by radiometric or color modifications. The ability of the proposed RRF filter to deal with these artefacts while restoring the fine details of images has been demonstrated on various examples. This approach can be used as a post processing for many classical image modification tasks, such as contrast and color transfer, movie restoration, gamut mapping, or high-dynamic-range (HDR) image visualization. In this work, a generic filtering method is proposed to suppress artifacts while preserving details. In this initially, a radiometric transformation is applied to a digital image & Streaming map which is the difference between original image and radio metrically transformed image is .Then the streaming map is regularized using a generic filter called RRF filter to remove the artefacts from color contrast modified images. The proposed method draws on the nonlocal Yaroslavsky filter to regularize the streaming map. The streaming map is filtered by averaging pixel values using weights

that are computed on the original image, therefore adapting to the geometry of this initial image. It will be shown that artefacts are progressively suppressed by iterating this filtering stage. The efficiency of the method can be shown on various radiometric modifications: contrast equalization, JPEG Encoding & Decoding. The visual artefacts can be minimized by using RRF filter compared to mean, median and wiener filter and it gives better results.

REFERENCES

- [1] A. C. Bovik, Handbook of Image and Video Processing, Communications, Networking and Multimedia, Orlando, FL: Academic, 2005.
- [2] C. Villani, Topics in Optimal Streaming. Providence, RI: Amer.Math. Soc., 2003.
- [3] E. Reinhard, M. Ashikhmin, B. Gooch, and P. Shirley, "Color transfer between images", IEEE Comput. Graph.Appl., vol. 21, no. 5, pp.34–41, 2001.
- [4] J. Morovic and P. Sun, "Accurate 3D image colour histogram transformation", Pattern Recognition . Letter., vol. 24, No. 11, pp. 1725–1735, Jul.2003.
- [5] F. Pitie, A. C. Kokaram, and R. Dahyot, "Automated colour grading using colour distribution transfer", Computer Vision Image Understanding., vol. 107, pp. 123–137, Jul. 2007.
- [6] Y.-W. Tai, J. Jia, and C.-K. Tang, "Local color transfer via probabilistic segmentation by expectation-maximization", in Proc. IEEE Computer Society Conference Computer Visual Pattern Recognition., 2005, pp. 747–754.
- [7] V. Caselles, J. Lisani, J. Morel, and G. Sapiro, "Shape preserving local histogram modification," IEEE Trans. Image Process., vol. 8, no. 2, pp.220–230, Feb. 1999.
- [8] T. Arici, S. Dikbas, and A. Altunbasak, "A histogram modification framework and its application for image contrast enhancement,"IEEE Trans. Image Process., vol. 18, no. 9, pp. 1921–1935, Sep.2009.
- [9] A. McCollum and W. Clocksin, "Multidimensional histogram equalization and modification," in Proc. Int. Conf. Image Anal.Process.,2007, pp. 659–664.
- [10] N. Papadakis, E. Provenzi, and V. Caselles, "A variational model for histogram transfer of color images", IEEE Trans. Image Process., vol.19, no. 11, p. , Nov. 2010.
- [11] J. Delon, "Movie and video scale-time equalization application to flicker reduction", IEEE Trans. Image Process., vol. 15, no. 1, pp. 241–248, Jan. 2006.
- [12] T. P. O. Rourke and R. Stevenson, "Improved image decompressionfor reduced transform coding artifacts", IEEE Trans. Circuits Systems Video Technology. 5, No. 6, 1995, 490–499.
- [13] Mei-Yin Shen and C.-C. Jay Kuo, "Review of Postprocessing Techniques for Compression Artifact Removal", Journal Of Visual Communication And Image Representation Vol. 9, No. 1, March, pp. 2–14, 1998.
- [14] Omprakash Patel, Yogendra P. S. Maravi and Sanjeev Sharma, "Comparative Study of Histogram Equalization Based Image Enhancement Techniques for Brightness Preservation and Contrast Enhancement", Signal& Image Processing : An International Journal (SIPIJ) Vol.4, No.5, October 2013.
- [15] G.A. Triantafyllidis, "An efficient algorithm for the enhancement of JPEG-coded images", Elsevier, Volume 27, Issue 4, August 2003.
- [16] L. A. Torres-Méndez and G. Dudek, "Color correction of underwater images for aquatic robot inspection", in Proc. Energy Minimization Methods Computation Vis. Pattern Recognition, 2005, pp. 60–73.
- [17] U. Lipowezky, "Grayscale aerial and space image colorization using texture classification", Pattern Recognition Letter, vol. 27, no. 4, pp. 275–286, 2006.
- [18] S. M. Pizer, E. P. Amburn, J. D. Austin, R. Cromartie, A. Geselowitz, T. Greer, B. T.H. Romeny, and J. B. Zimmerman, "Adaptive histogram equalization and its variations", Computer Visual Graph Image Process., vol. 39, no. 3, pp. 355–368, 1987.
- [19] A. Abadpour and S. Kasaei, —An efficient PCA-based color transfer method", J. Vis. Commun. Image Represent., vol. 18, no. 1, pp. 15–34, 2007.
- [20] F. Alter, S. Durand, and J. Froment, "Adapted total variation for artifact free decompression of jpeg images", J. Math. Imaging Vis., vol. 23, pp. 199–211, 2005.
- [21] L. Yaroslavsky, Digital Picture Processing, An Introduction. Berlin, Germany: Springer-Verlag, 1985.

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