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A survey on Retinex model based algorithms for Low light image enhancement

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***Abstract*—Low light image enhancement is an important task in making computer vision algorithms work robustly across the clock in all environments. This survey studies the existing work on the subject. The techniques for the task can be divided as classical image processing (histogram and retinex methods), machine learning techniques or hybrid techniques. This paper presents a review of the algorithms from all these categories along with datasets used to experiment them on. On conclusion, the paper suggests possible future research avenues.**

***Index Terms*—computer vision, image processing, low light enhancement, retinex model, neural networks**

I. Introduction

Photography came into existence as a way of preserving proof of perfect moments [1]. Earliest photographic systems were limited to cameras capturing monochromatic images in a narrow set of conditions. But they grew to sophisticated systems with cameras supported by post processing algorithms capable of capturing images across visible light spectrum and beyond (increased spectral resolution and range) on a wide array of conditions such as closer and further objects (zooming capabilities), fast moving objects (improved shutter speeds) and very dim objects (improved light sensitivity). One of the major concerns when taking pictures is the availability of light in the object. There are certain cases where the images are taken in low light conditions. As a result, the pixel values of the low light parts lie in a small lower color range. This makes the pixels values to fall in the noise range of the sensor chip. Thus, producing noise in the image when taking the image. Also, since the whole image appears very dark, it's hard to identify objects or textures clearly.

Therefore, it is vital to restore the features of the image. Image restoration can be broken into two subproblems as denoising and image enhancement. The former is concerned with the removal of external noise that affects the image, while the latter aims to enhance the quality of the image by making the features of the image clear and distinguishable. This survey focuses on the image enhancement problem as it is comparatively important in a low light scenario.

The algorithms for image enhancement can be categorized as Histogram Equalization (HE), Retinex theory-based methods and Dehaze model-based methods. Histogram Equalization methods keep the relative relationships among pixel values consistent and try to make them obey uniform distribution. Retinex theory-based methods compensate the illumination image through estimation and remove them to realize the image enhancement. Dehaze model-based methods which invert low-light images and apply dehaze method on them. We mainly focus on the retinex based algorithms as it has been used more consistently in multiple researches.

Recently, convolutional neural network (CNN) achieved impressive progress in several computer vision applications. Three methods mentioned above can be embodied in CNNs for low light enhancement. CNNs can learn to filter low-light images with different kernels and then combine multi-scale feature maps together to generate enhanced images. These CNNs were able to reconstruct more accurate image textures.

In this survey these retinex based algorithms will be discussed and compared as shown in Figure 1.

The rest of the paper is organized as follows. In section II, the System Model is introduced. Section III and IV discuss the classical solutions and machine learning (ML) based solutions respectively. In section V we discuss a set of hybrid solutions, which utilize ML to implement the derivations and modifications of classical solutions. Finally we conclude our study with the existing standard datasets which are used for experimentation.

II. System Model

The most consistently used model for image restoration or enhancement is the retinex model. The retinex theory [2] comes from the research done by E. H. Land and J. J. McCann in the field of Colour Vision. The retinex (the combination of words retina and cortex) is a model that explains the way the human vision perceives different colours under different lighting conditions. Through the results of the "Mondarian" experiment [3] Land suggested that the sensory signals from the same colours remains consistent regardless of the lightning condition and thus the colour perceived by the cortex remain constant. This feature of the human visual system (HVS) is known as colour constancy and it aids humans identify the same colours under different lightning conditions. However a computer system may perceive the same colour differently

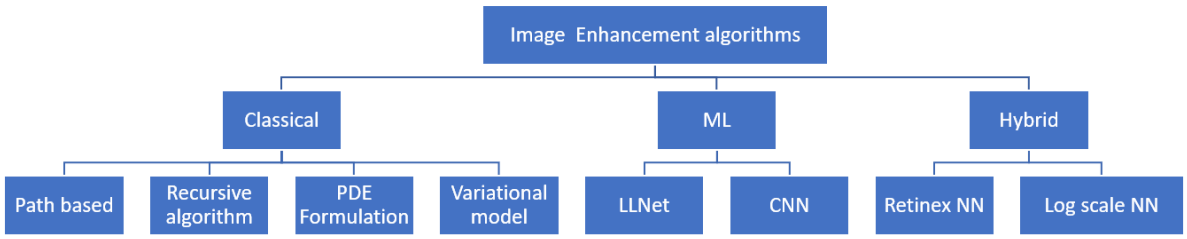

Fig. 1. Algorithm families for Low light image enhancement

under different lighting conditions. Thus the retinex model aims to mimic the color constancy property of the HVS through computer algorithm.

The retinex theory deals with the compensation for illumination effect in images. The primary objective of the problem is to decompose the image S into the reflectance image R and the illumination image L. Through this decomposition the effect of illumination on the image could be removed, but extracting the illumination from an image is an ill posed problem. Since the introduction of retinex theory, multiple methods have been proposed to estimate this illumination effect. However note that the estimation of illumination is not compulsory to solve this problem, as the illumination effect can be removed without estimating the illumination explicitly.

III. Classical Solutions

Many variations of the original retinex model have been proposed. Some of these proposed solutions are closer to the initial theory [3, 4, 5], whereas some others have made drastic changes but are still based on the same idea of retinex [6, 7, 8, 9, 10, 11]. The classical algorithms can be divided as path based algorithms, Recursive algorithms, PDE models and Variation models. Algorithms under each of these sections are discussed below. Note that under extreme low light conditions, these algorithms perform differently.

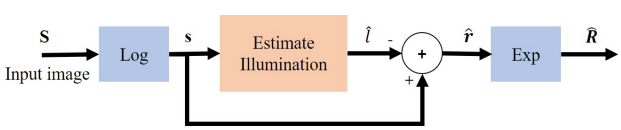

Fig. 2. Flow chart of Retinex algorithm

As mentioned before, the retinex model is to decompose the image S into the reflectance R and illumination L as $S = R * L$. The initial step of any retinex based algorithm is the same. The problem is first converted to the log domain as $s = \log S$, $l = \log L$, $r = \log R$ and thus $s = l + r$. This step is motivated both mathematically (preferring additions over multiplications), and physiologically, (referring to the sensitivity of our visual system) [3]. The different Retinex algorithms usually have the same flow chart as shown in Figure 2, however the method through which the illumination is estimated is different.

A. Path based algorithm

The original retinex model uses a path based algorithm. Path based algorithms consider the reflectance image by moving along the image pixel wise using single or multiple agents. The initial algorithm put forward by Land and McCann [2] were based random walks. A random walk is an algorithm in which the next pixel is chosen randomly and visited in order to update the value. In the proposed solution, a large number of walkers are initiated at random locations of an input image. These walkers update the accumulated value of the image as they walk alone. Finally the illumination is obtained by normalizing the accumulated values. In [4], Land followed up with different path geometry in which piece-wise linear paths are used. The random walk algorithm converges the accumulator value to a Gaussian average. This acts as a low pass filter and similar ideas have been used in future works even though the proposed methodologies differ. Later other path-wise alternatives were proposed. In [5], the authors propose modifications to the original retinex algorithm, including dual spiral pixel paths, a distance- weighting spatial multiplier, and a soft reset mechanism. Through experimental results, the authors show that the algorithm converges faster and provide comparatively desirable final output. However, most of these path-based solutions require manual tuning of fine parameters in order to obtain the desired results.

B. Recursive algorithms

Recursive algorithms were developed as an alternative for random walk in [12]. The path computation is substituted by a recursive matrix calculation and these recursive algorithms are more efficient than the path-based methods. However, the number of iterations is not clearly defined and the final results are strongly influenced by the iteration numbers set. Therefore, the convergence may not be guaranteed.

C. PDE based model

The retinex models make the assumption that the illumination image is spatially smooth whereas the reflectance image piece-wise continuous expect at the sharp edges of the images.

Through this reasoning, a PDE based model can be used estimate the illumination and decompose the image. Since the illumination varies smoothly the derivative values are low. The reflectance is piece-wise constant and discontinuous closer to the edges, and thus it's derivative vanishes everywhere (zero) except for the peaks that occur along the edges. By considering the derivative of s = l + r and then clipping out the peak derivative values, we can extract the illumination image assuming that the clipped values correspond to the peaks at the edges of r. Similar to previous methods the clipping acts as a low pass filter to solve the problem. The solutions are based on Poisson equations which can be implemented using Fast Fourier Transform (FFT) algorithm.

In [6], Horn applies the Laplacian to obtain the Poisson equation and after clipping the peaks suggests an iterative procedure that effectively inverts the Laplacian to solve the equation.

In [13], Blake introduced an improvement to Horn's method. He proposed to extract the discontinuities from the image gradient magnitude instead of the Laplacian and thereby came up with better boundary conditions that deal with less trivial scenarios along the image boundary.

There are other similar methods such as those of Morel, Petro, and Sbert [14, 15]. Using the same assumptions (the gradient of the illumination is relatively small), the threshold function was first applied to the gradient component-wise and then the Poisson equation was obtained by considering the divergence.

All PDE formulations have the following similarity : the formulation uses the logarithmic form of the original model and it considers the gradient with the assumption of piece-wise continuity to extract the reflectance image.

D. Variational models

In [7] Kimmel et al. propose a variational moddel for the retinex. Through physically motivated considerations the authors define a retinex reconstruction. The variaitonal problem is converted to a quadratic programming (QP) optimization problem. The QP problem is then solved using an accelerated project normalized steepest descent (PNSD) algorithm which exploits the knowledge about the spatial smoothness of the illumination. The PNSD algorithm uses a multi- resolution reconstruction of the illumination with few relaxation iterations at each resolution layer. It estimates the coarse layer first and expands the estimation to other layers through interpolation. The QP problem is initially formed by defining the optimal illumination as the solution and the authors show that this proposed formulation is a mathematically well-posed problem.

A variational model which uses two special bilateral filters is proposed in [8]. One is user for the evaluation of illumination and the other to compute the reflectance. The author proposes a non-iterative retinex algorithm that handles better edges in the illumination, and suppresses noise in dark areas. A sequence of similar convolutions is used to speed up the algorithm.

In [10], Ma and Osher have established a total variation (TV) regularized formulation and a non-local TV regularized formulation and an effective computational algorithm for these models based on the split Bregman method. Through numerical results the authors show that the proposed model is more effective than the PDE based solutions and the regularizer is better than the one proposed in [7].

In [9] Ng and Wang proposed a modified TV model for Retinex which overcomes the shortcomings in the models proposed in [7] and [10]. The TV model disregards assumptions of the continuity of the reflectance and considers a specific reflection function. This makes the proposed model more appropriate and reasonable for the decomposition. Furthermore, as opposed to Ma and Osher some constraints and a fidelity term are included in the proposed energy functional.These constraints and the fidelity term guarantee the existence of the solution for the proposed model through which can be shown through theoretical analysis. To solve their model, alternating minimization method is adopted. The model is divided into two subproblems which are solved by the split Bregman method and the FFT, respectively. Finaly the authors illustrate the effectiveness of the proposed model through numerical examples.

IV. Machine learning

Machine learning techniques have experienced an increase in interest during recent times. The popularity of using neural networks for image processing came after breakthrough techniques such as convolution neural networks (CNNs) [16], auto encoder networks [17]. In recent years, neural networks have been proved to perform better than classical algorithms in many image processing tasks [18, 19]. As such the neural networks have been introduced for low light image enhancement problem as well.

LLNet [20] is one of the initial method using deep neural networks to enhance low-light images. The network is a variant of the stacked-sparse denoising autoencoder using a multi-layer perceptron. Authors use a non linear transformation to generate training data for the proposed neural network. This method is further improved by Chen et.al [21] by building datasets of raw short-exposure low-light images, with corresponding long-exposure reference images and develop a network to learn the enhancement function. But the results perform well only on the constructed datasets.

Recently, convolutional neural network (CNN) achieves impressive progress in several computer vision applications. As to low-level image processing applications, CNN makes several breakthroughs in super resolution [22], image denoising [23], etc. In these problems the pixel values in degraded images are around the true values, and the average pixel values almost doesn't change. But in low light image enhancement problem, the range of the pixel values varies. Also, for low-light image enhancement, texture preserving is more important and the brightness is allowed to be fluctuant around the ground truth. Therefore, the loss function should captures these features in order to converge to a good solution.

These characteristics can be modeled using CNNs and other deep learning techniques to obtain best performance for image

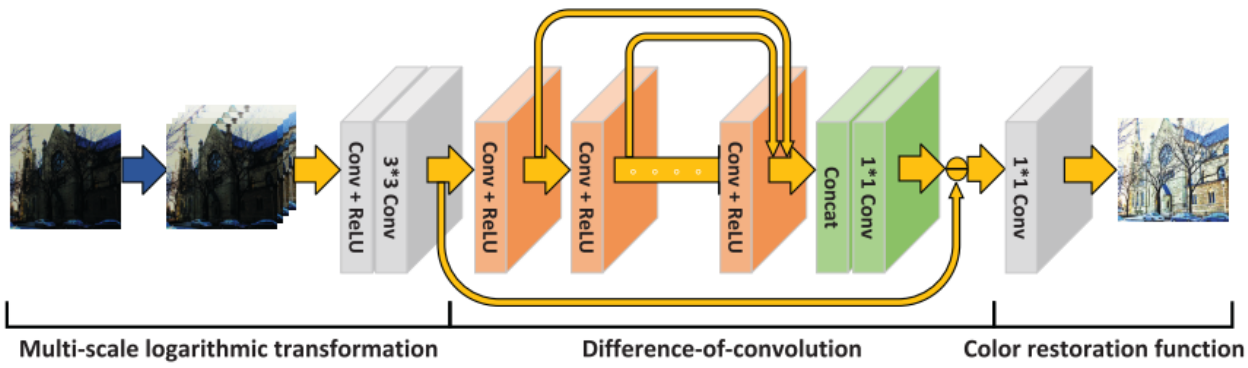

Fig. 3. MSRnet architecture

enhancement. Using different filters and residual connections it is possible to combine multiscale feature maps together to generate enhanced images. These residual connections preserve original features and textures. Also using a loss function that depends on the structural similarity, these textures in the image can be retained. Furthermore, deeplearning can be used to merge low level preprocessing steps like denoising into the model using a deeper pipeline. This can replicate some of the classical methods like retinex decomposition in a more generic way. These methods are discussed in the next section.

V. Retinex aware machine learning solutions

It was evident that both classical techniques and machine learning techniques have different strengths and weaknesses. Therefore an approach was developed to merge both these schools of thought. The work in this domain attempts to merge convolution neural networks [16] with (1) Retinex model (2) Log domain (3)Wavelet transform.

A. Retinex model based neural networks

Retinex model's flowchart suggests that the image should undergo a decomposition to the reflectance and the illumination (of same size as the image), each of them undergo different image processing steps (denoise the reflectance and amplify the illumination) and then be merged into one image.

LLCNN [24] draws motivation from Inception architecture [25] and Resnet [26] architecture. LLCNN uses *convolution blocks* in its pipeline similar to inception. The idea of residual connections from resnet are used to give two separate paths for reflectance and illumination. The 1x1 convolution (which was first put forward in inception architecture) is present in LLCNN.

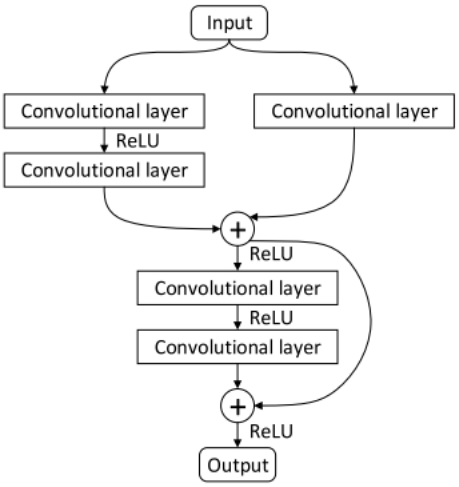

Fig. 4. LLCNN convolution block with residual connections

As shown in Figure 4 the LLCNN residual connections are shorter than the two pathways proposed in the retinex flowchart. This can be both advantageous (able to learn several iterations of Retinex like light enhancement) and disadvantageous (cannot perform a complete Retinex like light enhancement).

B. Log scale NN solutions

A solely neural network solution cannot mimic the transformation between the RGB scale and the log(RGB) scale. Therefore an explicit log transform was introduced to the NN pipeline starting from MSRnet architecture [27].

MSRnet proposes transforming the RGB scale to multiple ranges in the log scale to create a higher dimensional representation of the image consisting of the RGB scale and all the log scales. This higher dimensional *image* is fed into two pipelines (one a *residual like* connection and another with multiple convolution steps). The results (reduced to 3 color channels) are merged at the end and undergo a color restoration operation as shown in Figure 3.

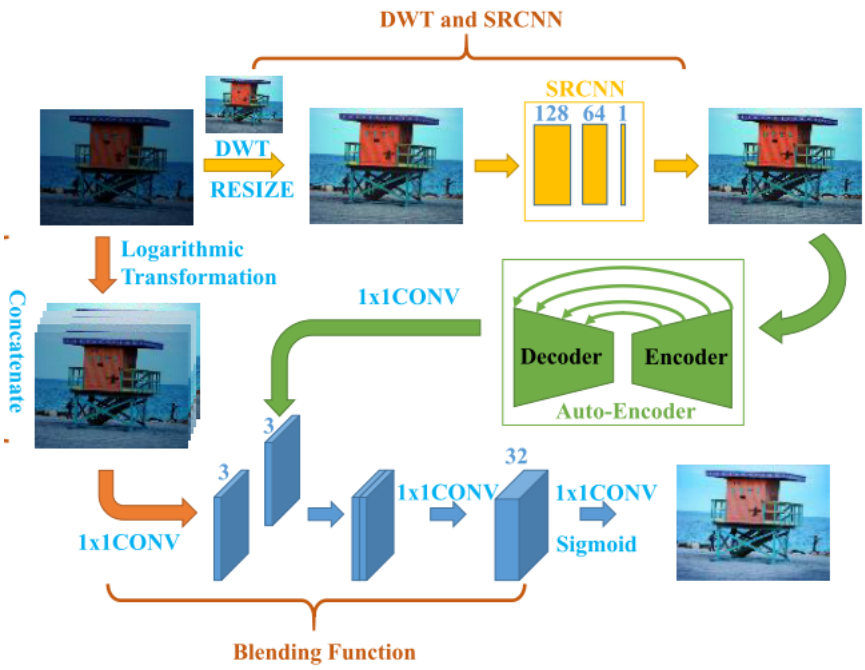

Fig. 5. Wavelet transform aware neural network

C. Wavelet transform

Wavelet transform (discrete version applied across spatial domain) is able to extract information out of the image [28]. This idea is used in [29] as another pathway between the input image and the output in the neural network. This allows the neural network to take use of another classical image processing technique to improve it's performance as shown in Figure 5.

VI. Existing datasets

The previous work use several types of datasets as,

1) Datasets with actual low light and high light images of perfect alignment. These datasets are captured by a tripod held camera facing a still object infront of static backgorunds. The two images are captured by varying the exposure time, aperture or flash. [21]
2) Datasets with minor misalignment between low light and high light images. This might be a result of handheld camera, moving objects or dynamic backgrounds. e.g. Google HDR dataset [30]
3) Synthetic datasets created by reducing the light in high light images. The light reduction is done by gamma adjustment. Furthermore, noise is added to make the low light images more realistic. e.g. LOL dataset [31]
4) Datasets with dark images only. These datasets cannot be used to train supervised learning algorithms. e.g. Exclusively dark dataset [32]

The availability (and the difficulty of creation) of datasets dictate the research directions for a problem. Type (1) and (3) are suitable for standard supervised learning. There are only few datapoints in (1). Eventhough (3) can act as a remedy for this situation, such trained algorithms do not perform very well in the real testing scenarios. We strongly suggest future researchers to collect sizable datasets of type (1).

Datasets of type (2) require sophisticated algorithms to correct the misalignment. But collecting this type of data is easier compared to (1). The misalignment could be minimized with faster image sensors and better image storage buffers.

Type (4) could be used for unsupervised (or semi supervised) learning techniques for low light enhancement. These datasets are suitable for classical signal processing techniques that do not depend on learning. It is very easy to collect type (4) data. But this is the most difficult dataset to develop algorithms on.

VII. Conclusion and Future work

The enhance of Low light images plays an important part in image processing. As a vital preprocessing step in many use cases, the enhancement of low light images plays a vital part in affecting various fields. Since the introduction of retinex model, the field of image enhancement has seen vase improvement. The increasing interest in machine learning has also helped in boosting this field. However, certain limitations still exists which should be studied in detail in the future.

The first and foremost limitation is the use of the retinex model which is based on certain assumption. The performance of these proposed methods in environments which violate these assumptions are poor. Therefore, eventhough these propose model improve in performance with each modifications, the need for a better model should be identified. Apart from this there are other considerations such as the efficiency and effectiveness of the model in dynamic conditions. It should be

noted that it would be a tedious or maybe an impossible task to develop a model that would performs well irrespective of the environment.

Furthermore it should be noted that this area of study is not independent and can be associated with other related studies such as object identification in low light condition and video processing in low light. However, the solution for these problems are specific and finding a generic solution to all these problems may not be impossible. Therefore, studying each of these problems separately is important in order to obtain the best performance.

Finally it must be observed that the methods listed here are based on standard dataset which were obtained using standard cameras and well defined conditions. It should be noted there is another field of study which studies the modification in hardware which can be done in order to solve this problem. Therefore future studies must concentrate on studying the ability to achieve optimal performance and increase the efficacy of the output by combining the hardware and software solutions.

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