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Enhancement and Segmentation of Low-Light Images Using Illumination Map Estimation based Level Set (IME-LS) Method

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Abstract— One of the most difficult aspects of image segmentation is that it cannot be successfully segmented if the image is dark or degraded. In this paper, proposes a method for the segmentation of low-quality and degraded images is put forth which is called Illumination Map Estimation based Level Set (IME-LS) Method. This proposed model has been classified into two parts: Firstly, we use an enhancement approach using illumination map approximation to enhance the input image. In this approach, Illumination map is constructed then refined. The refined illumination map undergoes an Augmented Lagrangian algorithm and then we use a sped-up solver for a considerably more efficient outcome. Secondly, Then the segmentation procedure begins once the image is enhanced. The enhanced image is segmented using level set bias method through Fuzzy clustering. In this method we employ the Fuzzy C-Means (FCM) algorithm to categorize data points into clusters. The fuzzy C-Means algorithm separates different entities in the image based on their varied intensities and sorts them into various clusters. The level set bias approach then tracks the variational boundaries of the image. We have designed the integrated algorithm in such a way that the image is classified or grouped into various clusters using a novel fuzzy Clustering algorithm and the variational boundaries of those clusters are tracked by employing the level set algorithm. In this paper, we further perform quantitative and comparative analysis of the suggested technique with respect to other segmentation techniques to illustrate the efficiency and flexibility of the suggested model.

Keywords: Segmentation, Fuzzy Clustering, Sped-up Solver, Illumination map, Level set approach.

I. INTRODUCTION

Generally, perceptual quality and visual precision of the images obtained in dark conditions are substandard. One cannot obtain clear details from such degraded images which affects the performance of various computer related tasks like object tracking and detection etc. Image enhancement and segmentation play a crucial role in improving the perceptual quality and concomitantly aiding in various computer related vision tasks. Methods

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for accurately detecting and recognising objects are required in the field of autonomous vehicle and artificial intelligence (AI)-based robot technologies, and the importance of semantic segmentation has risen as a result. Semantic segmentation is a method of classifying each pixel in an input image into a predetermined class.

The majority of current studies on semantic segmentation demonstrate strong performance during the day but noticeably poorer performance at night. Due to the lack of outside light, image brightness is typically very low at night, and camera sensor noise also rises. Additionally, the long exposure time of the camera results in images with motion and optical blur. Due to these problems, semantic segmentation is very challenging in low-light settings, and performance improvement is a challenging problem. Enhancement of an image improves the visual quality of a degraded image and also brings out the details of the image that were previously hidden which in turn produces effective segmentation results and makes the image desirable for various computer-based applications. There exist many approaches of image enhancement some of them are enhancement based on Histogram Equalization (HE), Retinex based techniques and Data driven algorithms [1].

Image Segmentation is widely used across numerous applications some of which are image extraction based on content, Machine Vision to extract information automatically, in medical field for the location and detection of lumps and tumours etc. This image processing technique segments the image into various partitions known as image objects or regions.

This process is generally employed to locate boundaries and entities in images. There exist many approaches for segmentation of an image, some of them are thresholding methods, Histogram based methods, clustering methods, level-set methods etc. In this paper, we employ a novel technique to enhance and bring out the details of a low light input image and then further segment the enhanced image to classify the details of the image using level set method in order to make it more meaningful, simpler for further analysis and desirable for various applications [2].

As a result, various methods for object segmentation in low light or at night have been investigated. In handcrafted feature-based segmentation studies, segmentation is performed in a low light environment by classifying the single object region as foreground and the rest of the areas as background. In this case, the background region is distinguished from the foreground region using unique handcrafted features of a single target object (foreground), resulting in a relatively better and more accurate segmentation performance. However, because the algorithm or filter is designed by hand, performing segmentation for multiple objects at once is extremely difficult in handcrafted feature-based methods. As a result, most studies have focused on the segmentation of a single object.

Low brightness, on the other hand, causes the colour information to vanish in conditions with very little light, and noise and blur change the shape information of objects in the images. There are currently not enough features available that are appropriate for classifying objects in images. To overcome these draw backs, we proposed a newly hybrid approach for accurate segmentation based on enhancement image. This method is a integration of pre-processing using illumination Map estimation (IME) for image enhancement and next stage segment image according to enhancement of image.

This paper is organized as following, literature review on enhancement and segmentation methods are explained in section II. Section III describes the proposed method and its mathematical implementation, section IV and V explained clearly simulation results and its discussion and conclusion respectively.

II. LITERATURE REVIEW

There are many traditional methods that were employed for segmenting and enhancing an image. There are several techniques for image segmentation, some of them are thresholding techniques, compression-based techniques, Histogram based segmentation techniques, level-set techniques etc. And out of various enhancement techniques, there are Histogram based enhancement techniques, Retinex based techniques, Data driven techniques.

Histogram Equalization is a renowned algorithm employed in numerous image processing models to improve the contrast and quality of the degraded image. [3-5] illustrate Global HE techniques that use the information of complete image's histogram to estimate transformation function. Whereas, [6-7] illustrate Local HE techniques that employ a window which moves upon the low-quality image and merely regards pixels in it for enhancement. As much as these methods prove to be useful in enhancing a low-quality image, they have their own set of drawbacks, like they increase the contrast of noise in the background, produce unnatural images, and also the computational cost is high.

Retinex theory-based techniques tend to increase the quality and intensity of the low-quality image by employing compression across the dynamic range. [8] Employs a weighed model to approximate the reflectance and illumination of the image and retain the structural details of low-quality image. enhances the low-quality input by employing illumination map of the image. This smoothing method is very efficient structure aware technique that was introduced to increase the consistency of illumination of the image. Initially evaluates the illumination map of the input and then the structure of image's illumination is exploited to obtained a refined output. This technique is known to efficiently enhance a low-quality image.

Data Driven Enhancement Techniques have become very popular and are actively used in enhancement of a low-quality image. In [9] a hybrid trainable network via deep learning is used for the enhancement of a low-quality image and it employs two distinct streams namely edge stream and content stream to restore the outlines and details of the low-quality image. The outcome obtained through this state-of-art method is slightly realistic, but lacks in proper resolution, computational complexity is more and is not flamboyant in comparison with many other futuristic methods.

Level-set approaches are one among the most effective segmentation approaches. This kind of numerical approaches are demonstrated in [10-12] and are mostly being used to solve the issues related to curves or surfaces and are extensively used in medical field for segmentation and location of pathologies. [13] chan-vese mode illustrates a flexible active contour segmentation model based on evolution of a curve and energy minimization that can segment the areas of interest which do not possess clear boundaries.

Despite being useful across many applications it has limitations like it produces results with mediocre accuracy and also computational complexity is more.[14] propounds a DRLSE technique applied to an active contour pattern based on the edges for segmentation. DRLSE is formulated on formulation of level set and narrow band realization which allows flexible initialization. It employs fair amount of time steps to minimize iterations and complexity or time of computation. But nevertheless, this approach tends to have comparatively more computational cost and time complexity.

The technique used by B.N. Li et al. illustrates an automated data driven level set approach that employs fuzzy clustering algorithm. Bing Nan Li et al. Presents a robust technique that employs spatial data in order to estimate the concerned boundaries and required parameters automatically and it also stops boundary leakage. This approach prevents inefficient segmentation of an image. But this approach does not yield satisfactory results in case of a degraded or low-quality input images.

In this research, we propound an advanced algorithm that can efficiently segment low-quality and degraded images. The proposed method makes use of two processing steps to enhance and bring out the details of a degraded image and then segment the enhanced good quality image to classify the objects in the image effectively.

III. PROPOSED METHOD

We propose a flexible and efficient image processing model which consists of two integral processing steps as shown in Fig. 1, in order to effectively segment a digital image under low light intensities. The proposed model is diversified into two stages such as pre-processing and post processing respectively.

In pre-processing section, we enhance the low-quality image using an image enhancement technique known as lowlight Illumination Map Estimation (LIME) method to bring out the details in the degraded image. Then in post-processing section we further employ a constructive level set approach integrated with fuzzy clustering to segment the acquired enhanced image. The detailed implementation of pre-processing and post processing stages are explained in following sections.

A. Pre-Processing - Enhancement using Illumination Map Approximation (IMA) Method

The model of our concern is comparable with that of natural image decomposition model which endeavors to deteriorate the contribution to two parts. We can obtain our result by decomposing out low light image into two components i.e., Reflectance and Illumination components. But there is a limitation using reflectance component. The object loses its shape or some of its boundary, which doesn't fulfill our objective. The point of this pre-processing section is to retain the visual substance of dull districts as well as keep the visual authenticity and this model resembles the algorithm which is illustrated in [15].

The unrealism of involving reflectance as upgraded outcome was endeavored to extend the adjusted brightening back to reflectance. The ideal aftereffect of upgrade is acquired by some way or another consolidating the decayed parts once more.

As for our paper concerned, similar to the model illustrated in [15], there is no requirement of decomposing the image into both Reflectance and illumination components. In this paper, we only work with illumination map. In Retinex model [16] for image enhancement, the formation of low light image is described as follows

$$L = R \circ T \tag{1}$$

where, L is the low light input image, R is the required enhanced output image and T is the illumination map. The $\circ$ operator refers to element wise multiplication. By slightly modifying the equation (1), we get

$$R = L / T \tag{2}$$

So, the illumination map T is the key to get the desired enhanced output. The remark for exact solver to problem is convergence and optimality. This Algorithm we employ to find the perfect illumination map is Augmented Lagrangian Multiplier with Alternating Direction Limiting (ALM-ADM). In various expressions, our proposed genuine solver gives fitting results for the predetermined conditions.

For obtaining initial illumination map, we take the maximum value of all the three channels and replace that function in equation (1).

$$\hat{T}(x) \leftarrow \max_{c\in\{R,G,B\}} L^c(x) \tag{3}$$

$$R(x) = L(x) / \max_{c\in\{R,G,B\}} L^c(x) \tag{4}$$

We get the refined illumination map T dependent absolutely upon $\hat{T}$ through our algorithm. Furthermore, we can perform gamma transformation on T through $T \leftarrow T^{\gamma}$. If $\gamma < 0$, it tends to be brighter. If $\gamma < 0$, there is no change between the original and result image. If $\gamma > 0$, the image becomes darker.

We perform the operation through Alternating Direction Technique (ALM). The optimization model is as follows

$$\min_{T,G} \parallel \hat{T} - T \parallel + \parallel W \circ G \parallel_1 \tag{5}$$

Here, $\hat{T}$ is primary illumination map, T is required illumination map, W is the Weight matrix and G is the First order derivative filter. Component wise multiplication among W and G is being implemented.

As we are employing, Augmented Lagrangian algorithm, it updates each and every variable one by one iteratively until we get the final illumination map. The illumination map is updated using the equation,

$$T^{t+1} \leftarrow F^{-1}\left(\frac{F\left(\mu^t D^{(T)}(G^t - \frac{Z^t}{\mu^t})\right) + 2\hat{T}}{\mu^t \sum_{x\in\{h,v\}} F\left(D_x\right) \bullet \bar{F}\left(D_x\right) + 2} \right) \tag{6}$$

where, $F()$ performs 2D FFT operation, $F^{-1}()$ performs 2D IFFT operation, $\bar{F}()$ is the complex conjugate of the function $F()$, μ is a parameter, D contains To eplitz matrices D_h and D_v, Z is the Lagrangian multiplier and G is first order derivative filer.

The illumination map T^{t+1} is updated by updating G^t, Z^t and μ^t one by one iteratively. G^t can be updated as follows

$$G^{(t+1)} = S_{\frac{\alpha W}{\mu^t}}\left[\nabla T^{(t+1)} - \frac{Z^t}{\mu^t}\right] \tag{7}$$

where, S is the shrinkage operator and ∇T is the first order derivative filter.

Updating Z^t and μ^t is as follows,

$$Z^{(t+1)} \leftarrow Z^{(t)} + \mu^t(\nabla T^{(t+1)} - G^{(t+1)}) \tag{8}$$

$$\mu^{(t+1)} \leftarrow \mu^t \rho, \rho > 1 \tag{9}$$

The algorithm stops iterating when $\parallel \nabla T^{(t+1)} - G^{(t+1)} \parallel_F \leq \delta \parallel \hat{T} \parallel_F$; $\delta = 10^{-5}$ or when maximum numbers of iterations are finished.

From this we obtain an enhanced version of the low-quality input image. The enhanced image acquired through this enhancement technique can be further denoised or recomposed by employing Bilateral filtering algorithm. From this part of processing, we acquire an enhanced and denoised good quality image.

$$R_f = R \circ T + R_d \circ (1 - T) \tag{10}$$

Where, R is the enhanced image, T is the illumination map, R_d is the image after denoising and R_f is the image after recomposing.

When it comes to the complexity of computation, there are 3 sub-issues in every iteration and each iteration takes $O(N \log N)$, where N the total number of pixels is. 2D FFT and IFFT operations require most of the time in the whole process. The total time complexity of the algorithm can be determined by $O(tN \log N)$, where 't' is the total number of iterations. This model is similar to the algorithm demonstrated in [1].

B. Post-processing – Integrating Fuzzy Clustering with Level Set Approach

In this section, primarily, spatial knowledge is consolidated by employing fuzzy clustering through adaptive versatile optimization, in which it disposes of intermediate morphological activities. Furthermore, parameters that are needed to control the flow of the algorithm are extracted directly through fuzzy clustering consequences, which is of level set segmentation. Moreover, one more procedure composed of this soft clustering is propounded to regularize the advancement of the level set [17].

To decrease cost function (predefined) centroid, as well as the scope of every sub-divided class, assessed adaptively in fuzzy clustering. The k means algorithm originated from classical FCM. In short, this algorithm looks to relegate N entities, which are centered on their properties, to form k sets, which are called clusters (K<N). In image segmentation number of images, and pixels are represented with N.

The ideal outcomes incorporate each cluster's centroid and the affiliation of N objects. To minimize the cost function endeavoring of k means cluster in the respective norm. The absolute consequence of the k mean technique expands the internal cluster diversification, yet curbs the intra-cluster diversity. This clustering algorithm is streamlined when elements of the image close tothe center point are

$$j = \sum_{m=1}^{K} \sum_{n=1}^{N} \parallel i_n - v_m \parallel^2, \quad (11)$$

Where $i_n$represents a particular image pixel and v_m represents the m^th cluster's centroid and || denotes the appointed high participation values, while they are far away and are allocated low qualities. Since the image commotion and ancient rarities frequently debilitate the presentation of FCM segmentation, integrating spatial data into an FCM would be appealing.
The FCM cost function which is similar to the previous function

$$j = \sum_{n=1}^{N} \sum_{m=1}^{C} \mu^l{}_{mn} \parallel i_n - v_m \parallel^2, \quad (12)$$

Where l, which is greater than one is a parameter that controls resultant segmentations fuzziness and μ_{mn} is the membership function.level set techniques use variational limits that are dynamic for segmentation of the input. Intensive computation is the major concern regarding level set segmentation and the function associated with it converts image segmentation problems from 2D to 3D.

The fuzzy level set algorithm is similar to [18] model and it mechanizes the initiation and boundary setup of the segmentation model, utilizing FCM. That is, an FCM which is restricted spatially is employed to decide the inexact contour concerned in an image. For evolution, FCM can directly accommodate with level set function which is enhanced. There are certain controlling parameters to be configured necessarily. These parameters are tuned automatically using fuzzy clustering. The function $\xi(g,\phi)$ integrates the information of the gradient of the corresponding image through,

$$\xi(g,\phi) = \lambda\delta(\phi)div\left(g\frac{\nabla\phi}{|\nabla\phi|}\right) + vg\delta(\phi), \quad (13)$$

Here $\delta(\phi)$ represents Dirac Component. Distinct contributions of these components are administered by v, μ and λ which are non-changing parameters. Fundamentally, $\xi(g,\phi)$ draws ϕ in along the variational limits. But, $\zeta(\phi)$ penalty term forces ϕ distance function approached automatically [19].

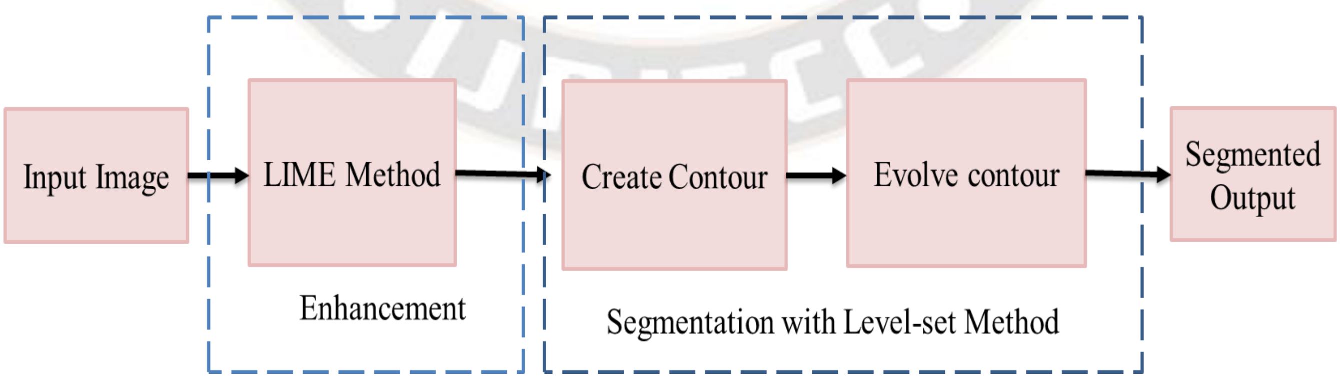

Figure 1: Control flow diagram of the Suggested model.

C. Algorithm Steps of Proposed method

Step-1: Assuming the perfect illumination map is the key for our model to obtain enhanced image. The most efficient model is given in eq. (5).

Step-2: Initialize $T^{(0)} = G^{(0)} = Z^{(0)} = 0$, where, $G = \nabla T$ and Z is LaGrangian Multiplier.

Step-3: Update the three variables T, G and Z till the image is converged and While (check image is converged),

Yes => exit the loop

No => Update T using (6).

Update G using (7).

Update Z using (8).

Update μ using (9).

Step-4: First, we employ the algorithm 'Fuzzy C-Means'. It classifies the image on the basis of subclasses (regions with almost constant intensities).

Step-5: Convert the image into grayscale and perform adaptive noise filtering and iterate a loop with maximum iterations.

Step-6: Estimate the distance between the Centre point and the boundary of every subclass to find the scope of each subclass and Initiate Level set function on our regions of interest. If R_i is region of interest, then the level set function is

$$u(x,y) = -4\varepsilon(0.5 - B_i) \qquad (14)$$

Where ε is referred to as Constant of Dirac function and B_i is the Binary image.

Step-7: The image is classified by Level Set function into distinct parts with respect to the condition of $u > 0$ or $u < 0$.

IV. RESULTS AND DISCUSSIONS

In this section, we focused on simulation results and its discussion of the proposed method as well as conventional methods. In this work, we proposed Illumination Map Estimation using Level set (IME-LS) Method for robust segmentation of real world low light images. The proposed method needs four controlling parameters for efficient enhancement of images during image pre-processing with the help of Illumination Map Estimation (IME) algorithm. The Optimal controlling parameters and their corresponding values for each image where, 'ds' is the extent of smoothing, 'ss' depicts smoothing parameter in case of bilateral filtering, while 'mu' and 'rho', are constant parameters for the solver (see table I). These parameters are determined using trial and error method and when tuned accordingly produce efficient and accurate enhancement results. Similarly, we required four controlling parameters such as C, **σ** , **μ** and T (see table II) are Controls the strength of the gradient of primary LSF , Specifies and regulates the size of neighbourhood , Coefficient of regularization term and Total number of Iterations respectively. These parameters are necessary to control boundary leakages using level-set model in the post-processing stage. We use synthetic and real images to test the proposed model's segmentation performance over conventional level set methods such as C-V model and DRLSE model respectively. The experimental outcomes of segmentation acquired using the propounded technique is compared with results acquired from few other futuristic models of segmentation along with Chan-Vese [13] technique and DRLSE model [14] and the functioning of the suggested segmentation model is analysed with respect to these futuristic techniques. The dataset employed in the model presented in this paper is taken from GitHub. The proposed segmentation model is implemented using MATLAB R2021a software in a windows® system (Microsoft) with 4CPU 2.40GHz and 8GB RAM. In this paper, we consider a total of 8 images and implement our algorithm and a few other existing algorithms on these images. Then we evaluate the outcomes acquired from the suggested model, with respect to existing segmentation techniques regarding parameters like number of iterations, time complexity etc.so as to exhibit the significance and robustness of the suggested technique over the existing ones.

The Fig.2 represents the comparisons between the segmentation results obtained through proposed technique and other existing methods like Chan-Vese and DRLSE techniques. In Fig.2, the column (a) represents all the source images or low-quality input images, column (b) shows the images that are enhanced using LIME technique in pre-processing part, column (c) depicts the enhanced images that are further denoised using Bilateral filtering, column (d) depicts the segmentation results acquired through Chan-Vese technique, column (e) depicts the segmentation results obtained via DRLSE model and finally column (f) represents the segmentation results obtained via proposed technique.

From Fig. 2, we can see that, the proposed segmentation technique yields better segmentation outcomes than Chan-Vese technique [13] and DRLSE method [14]. It is manifested from the above results that Chan-Vese model performs poorly on low-quality

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images and fails to classify absolute details or objects in the low-quality image and can merely segment a part of the low-light image. Identically DRLSE method as well performs poorly on the degraded input images and fails to segment the ground truth image. On the contrary, proposed technique effectively segments the boundaries and edges of objects or details in the input image.

There exist few parameters that control the level of enhancement and segmentation of an image known as controlling or optimal parameters. Precise tuning of these parameters is needed in order to obtain accurate and admirable enhancement and final segmentation results.

Table I depicts Optimal controlling parameters and their corresponding values for each image where, 'ds' is the extent of smoothing, 'ss' depicts smoothing parameter in case of bilateral filtering, while 'mu' and 'rho', are constant parameters for the solver. These parameters are determined using trial and error method and when tuned accordingly produce efficient and accurate enhancement results.

Table II depicts necessary parameters that control the post-processing level-set model. Unlike pre-processing LIME model where the hyper parameters are determined using trial and error, the post-processing model employs fuzzy clustering technique to determine the parameters automatically and accurately without any human intervention.

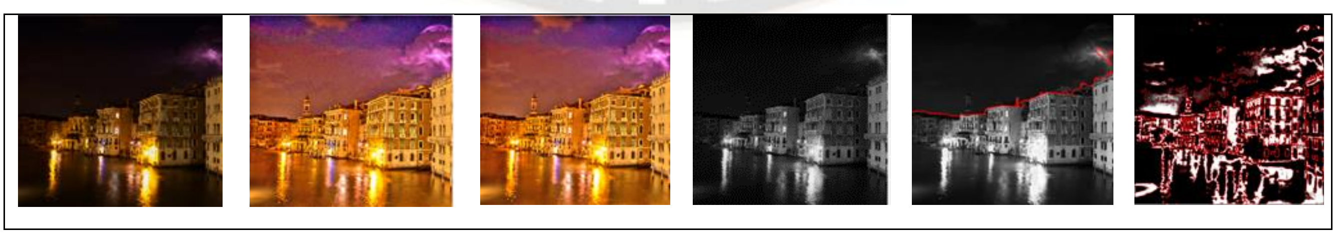
From Table III, we can notice that the computational complexity of propounded method is significantly lesser than Chan-Vese and DRLSE methods. That is, Chan-Vese model and DRLSE techniques require more time to produce the segmentation results. From Table 3, It can be inferred that that the proposed technique yields efficient and satisfactory segmentation results with a smaller number of iterations i.e., with only 200 iterations.

Whereas, the Chan-Vese algorithm makes use of 1000 iterations and DRLSE algorithm employs 3760 iterations to produce a segmented result. Despite taking more time and employing a greater number of iterations the existing methods like Chan-Vese (C-V) and DRLSE models fail to produce satisfactory results compared to propounded technique, when applied to degraded images.

Finally, we stated that this proposed research work suitable for synthetic and real work poor illumination images to enhance the object details effectively in the pre-processing stage and also four parameters are required such as 'ds', 'mu', 'rho' and 'ss' respectively. The average values of those parameters for efficient enhancement of images are 3.55, 0.210625, 1.147125 and 1.23125 respectively. Similarly, accurate and robust segmentation using level set method in post processing of real-world low-light images based solely on image enhancement. In the level set method also required few controlling parameters to mitigate boundary leakages, according to Table III the average computation time in sec for both conventional and proposed methods are 12.53625s, 264.925s and 11.9075s respectively. We can see the average computation time values of C-V method and DRLSE method have high values over proposed method. The proposed level set method evolve the contour with average CPU time need is 11.9075s. For visual representation and parameters needed and its analysis, the proposed method has given superior performance over conventional level set methods for accurate and robust segmentation of low light images.

TABLE I.OPTIMAL HYPER PARAMETERS CONTROLLING ENHANCEMENT OF IMAGE IN PRE-PROCESSING LIME MODEL

Image	ds	mu	rho	ss
Building	10	0.01	1.118	1.5
Cars	5	0.045	1.134	0.75
Lamp	0.1	0.8	1.07	1
Land	0.3	0.5	1.09	4
Moon	1	0.01	1.2	0.5
Plant	1	0.3	1.15	0.5
Robot	10	0.01	1.25	1
Wires	1	0.01	1.165	0.6
Average	**3.55**	**0.210625**	**1.147125**	**1.23125**



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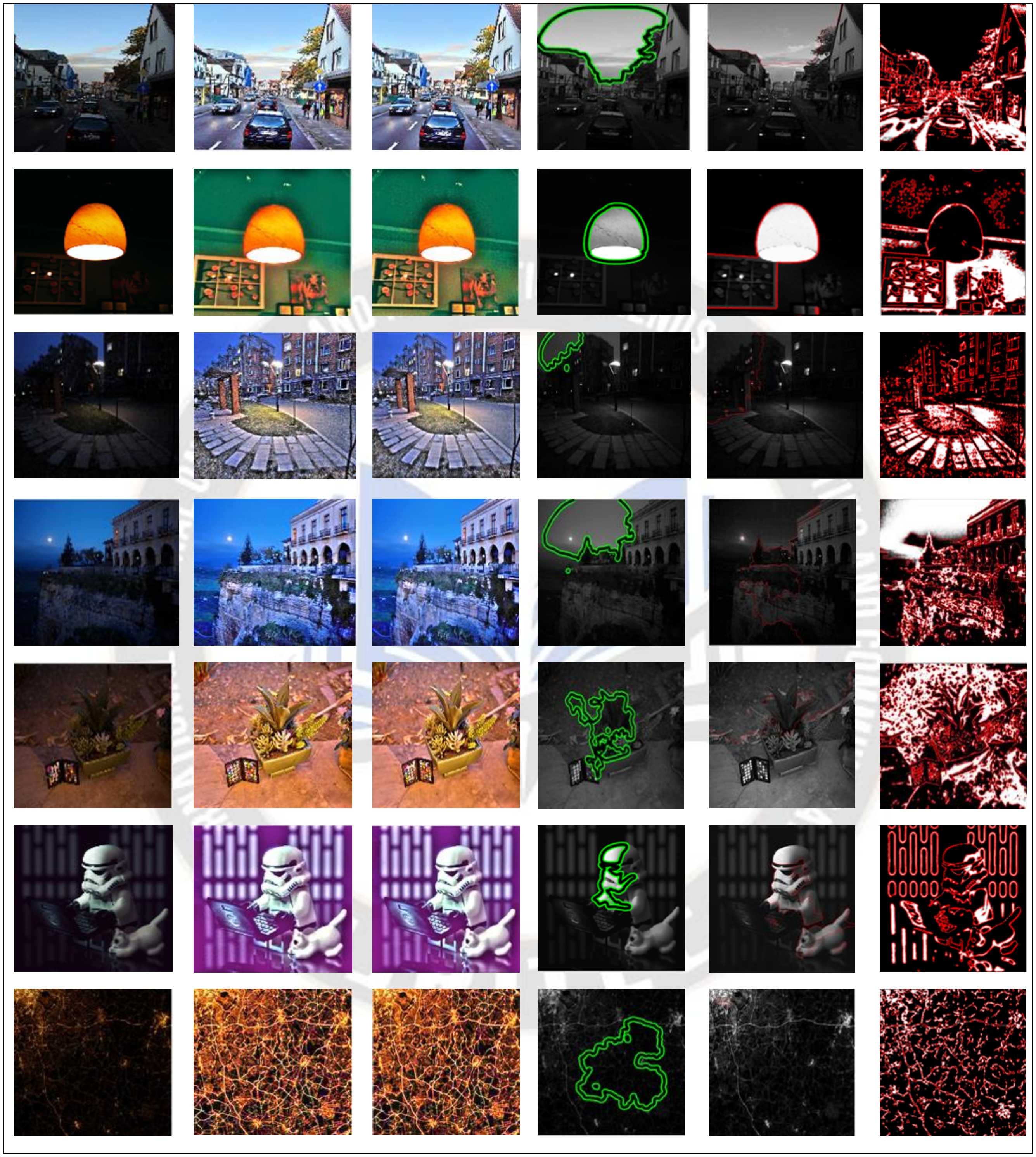

(a) **(b)** **(c)** **(d)** **(e)** **(f)**

Figure 2. Comparison of segmentation outcomes obtained from proposed segmentation technique with those obtained from existing methods. From (a) to (f): Low-Quality Input Images, Enhanced Images, Denoised images via Bilateral filtering, Results by Chan-Vese model, DRLSE model, and proposed model respectively.

TABLE II: OPTIMAL PARAMETERS THAT CONTROL THE LEVEL-SET MODEL IN POST-PROCESSING

Name of the Parameter	Importance of the Parameter
C	Controls the strength of the gradient of primary LSF
σ	Specifies and regulates the size of neighbourhood
μ	Coefficient of regularization term
T	Total number of Iterations

TABLE III . QUANTITATIVE ANALYSIS OF PERFORMANCE OF PROPOSED METHOD WITH RESPECT TO EXISTING METHOD IN TERMS OF TOTAL NUMBER OF ITERATIONS AND COMPUTATIONAL COMPLEXITY

S.No.	Image Number	Number of Iterations			Computational time in seconds		
		Chan-Vese model	DRLSE model	Proposed segmentation model	Chan-Vese model	DRLSE model	Proposed segmentation model
1.	Building	1000	3760	200	15.63	466.8	12.69
2.	Cars	1000	3760	200	9.29	131.6	5.45
3.	Lamp	1000	3760	200	9.20	196.5	8.97
4.	Land	1000	3760	200	29.9	703.2	35.5
5.	Moon	1000	3760	200	10.4	212.1	11.23
6.	Plant	1000	3760	200	8.84	171.1	9.14
7.	Robot	1000	3760	200	9.50	186.1	9.37
8.	Wires	1000	3760	200	7.53	52.0	2.91
				Average	**12.53625**	**264.925**	**11.9075**

V. CONCLUSION

In this paper, an accurate and effective enhancement and segmentation model is proposed in order to improve the perceptual quality and further segment low-quality degraded images. In the proposed segmentation model, we employed two significant algorithms: Enhancement technique using illumination map approximation to bring out the details of the low-quality image and level-set method with fuzzy clustering to further segment the image. The quantitative experimental and comparative results and analysis demonstrate on synthetic and real world low light images which are collected from Github open source database. Based on the assessment parameters and visual segmentation results of low light images, our proposed technique performs favourably when compared to many other conventional level set methods.

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