A New Method to Find Image Recovery

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Abstract*—Scattering media imagery is degraded during the physical process of image formation, which shifts contrast, color, and turns overall visibility white. With the computer vision system, sight can be amazingly restored. Although the medium transmission in distant artifacts is small, it is vulnerable to amplification of the noise. Here we present / propose the picture recovery of the L0 gradient, which solves the issue discussed previously. In comparison to raw images, the single image is processed and recovered significantly improves while noise amplification discards. The state-of-the-art studies on dehazing have been reviewed in this paper. In addition, L0-gradient minimization of image smoothing was studied in combination with H Kosmedier Image Formation Physical System to solve the dehazing issue as L0 smoothing approximates better results with higher false discovery rate (FDR) .Recovery using L0-Gradient Minimization is formalized in a depth chart that reduces noise adaptively to recover estimated structures marginally in spatially changing media delivery. The minimal gradient is non-zero. Therefore, noise and blur in the nearby objects with low measurement difficulty and impact have been effectively removed, raising the transmitting approximation contributing to the enhancement of the recovered image. We are experimenting with atmospheric, submarine, at night, indoor turbid medium images qualitatively and quantitatively.

***Keywords*—Computer vision; image enhancement; digital image processing**

I. Introduction

A hazy image is distinguished by poor light, dark, low contrast and color dispersion as well as blurriness, vibration and bland appearance under the images. When the atmosphere is turbid, including rain, vogue, smoke, pollen, and wind, the image quality is alarmingly influenced by low visibility. The dispersion of light is influenced by floating misplaced particles in the atmosphere. The radiance emerged from a scenario that decreases steadily from the point of view to the viewer and the dispersing light in the manner that transforms the background contrast, colour and intensity caught down. Visual information is collected with such poor visibility and is highly requested for tracking, navigation, computer vision, oceanography, flight surveillance. It is therefore extremely important either to mechanically restart programs or to evaluate them in real time. In order to solve this problem, several techniques were recommended. Hazy picture recovery differs from standard noise reduction and comparison. Haze influences the dynamic color spectrum in the image Methodiques for remote sensing, airplane boarding, steering, visual aided transportation, driver support device, image captured in the snow, fog, oceanography and many others are of great benefit in various applications. Because of this high demand, physicists invent new and effective inventions day and night. This is the new location in the field of research. The articles published in this region during the time 2000-2018 illustrate this. It's over a thousand men. However, due to the unique characteristic of haze, the research is still unified. In addition, haze image recovery is dependent upon additive as well as multiplier distance of the object and the acquisition device. Those result in the recovery model being completely un-positioned inversely and the optimization problem is constrained (Fig. 1). Few parameters are estimates that are discussed later. There are therefore many scopes for improving the model constantly in order to obtain a finer image.

(a) (b)

Fig. 1. Shows Natural Outdoor, where Haze Sample Hazy (a) and Haze Free Image (b).

The rest of this paper is organized as follows. Section II introduces the dehazing methods according to their classification in Fig. 3 and their principles and characteristics are analyzed in detail. In Section III, different eminent researchers in this field have been studied. Image formation model has been discussed with mathematical details in Section IV. In Section V, L0-Gradient minimization has been examined in detail. In Section VI, Application of L0-Gradient minimization in Image is discussed.

II. Classification of Image Dehazing Methods

Methods of decontamination are divided into three kinds: a) development, b) fusion of the image and c) restoration of the image. Dehazing focused on identity enhancement is not very necessary and is not really welcomed. Contrast and illumination partly strengthens. Dehazing focused on image fusion entails the creation of multiple images on multiple channels without a physical model. This methodology optimizes knowledge from the information provided in multiple channels. Dehazing Photo Restaurant uses optical photo simulation methods based on physics. Inversing the model and calculating certain parameters that induce the distortion is a way to obtain initial image radiance. In principle, three techniques of image restoration are available: a) supplementary information, b) multiple image, and c) prior knowledge. Our approach is based on an optical picture creation model based on previous information physics. Such method includes a single image that makes it the most complicated methodology among the modern technologies, but is the most popular in use because of its lack of information about the current image, i.e. the single image. This technique needs to remove the noise from the target to the installation of cameras, because pixel radiance deteriorates rapidly along with the loss of the so-called blur. Noise amplification is thus a particularly demanding problem during the inversion of the image recovery. Since the haze function is not standardized or constant and the radiance of the scene reduces gradually, the removal of noise will conform to distances. More than nearby objects, distant items are impacted. Tan [5], Fattal [6], He [7], Tarel [8], and Berman [9] are some state-of - the art algorithms for single image dehazing.

III. Related Work

Unconstrained problem is single image dehazing. In this class, dehazing based on prior knowledge has high potential and new algorithms are very promising. Our analysis is based on a single picture unraveling based on prior experience. The following is a significant piece of research under this section.

- 1998 Okley [3]: Daylight signal spread by an aerosol attenuating the gap from the illumination point to the sensor for each pixel. The concept was the reverse H Kosmeider dynamics model [1] and J Marcartney's model was enhanced [2]. Measurement of the signal to noise ratio. Temporary filter configuration that preserves the SNR constant regardless of distance is suggested. Major growth has been achieved. Previous knowledge of scene geometry was required in this procedure. Also restored was the low spatial frequency knowledge. This approach was the first re-search for an inverse pattern of picture creation to preserve visibility.

- Tan in 2008 [5]: one image dehazing based on two knowledge assumptions: i) a foggy image has less contrast than a clear day; ii) an object seen from a point of acquisition exponentially decaes due to air light and, by the presence of atmospheric particles, makes a distant object smooth and invisible because the light absorbs and scatters, modeled on a linear combination of direct attenuation and air light. Automated system and the need for a single image were the main advantage of eliminating all schematic details that rendered the process special. A random field-based cost function was developed that was efficiently optimized with credentials or graphs. A Markov random field based cost function efficiently optimized by belief propagation or graph-cut has been developed. The method is efficient as required single image, but not applicable for real time. The method suffers from “halo” effect due to abrupt depth change which leads to colour over-saturation.

- Fattel Approach [6] in 2008: R Fattal analysis on the basis of single image haze and dispersion light calculation. The knowledge has obtained hazelnut free picture contrast to improve clarity. Transmission and surface filtering have been believed to be uncorrelated locally. Simple statistical inference eliminates certain problems such as albedo level. This method's task is to address the pixels without any communication. Implicit graphical model allowed the solution of these pixels to be extrapolated. R Estimated fattal transmission chart for haze-free image. The dispersion of light to improve illumination is reduced. A latest optical paradigm, where ambiguities in the details are overcome by surface filtering and propagation, is locally irrelevant and effectively eliminates hazel layers and determines the precise color of hazel. Eventually, the system seeks the effective transmitting answer. Due to atmospheric diffusion the algorithm also suffers from blurriness.

- J Kopf [18] in 2008: The primary information included a deep photo system based on existing digital terrain. Hence, huge quantity of Terrain 3D modeling, texture, depth was collected. This information will speed up to rebuild the original color, structure, texture and details of the bright image. But the method is subject to costly system requirements, such as radar, etc.

- He method [7]: DCP (dark channel prior), a statistical prior to haze-free images, was used in certain research projects. This experimental reveals 75% pixels of every dark channel on a standard RGB picture where the lowest intensity channel from three RGB imaging channels is shown by an unknown band. 90% pixels of that channel are below 25. But in cases of degraded weather, the scenario drifts dramatically. This is similar to dark channel high intensity. Due to the atmospheric light, the pixel intensity is shifted to very high value and the image produces almost white. The method is efficient, but due to its high computational complexity, it takes a long time to replicate. Hence, a Dark Channel Prior (DCP) technique has been developed that is essentially beyond two other techniques mentioned above cannot be useful for real-time use. Throughout DCP, strong picture contrast is large and pixel intensities are spread across the whole spectrum evenly, but turbid weathered artifacts do not accurately allocate the intensities, move to the peak of the intensity scale and the image appears as white. This statement describes the central DCP patch and, in effect, determines transmission. Using the scattering model of an environment (see equation 2) the image eventually recovers. As already stated, the image is recuperated by an inversion in this disperse model which is affected by a substantial blocking effect in the map. By sparing laplacian matrix, the transmission diagram can be wisely calculated. The method is not ideal for rapid activity due to its high machine sophistication. This method is still quite satisfactory except for the uncomfortable performance.

- Method Tarel [8]: Fog, haze, smoke and outdoor images fade color and contrast make it difficult to process those images. J P Tarel's algorithm is fast and its difficulty is linear with the amount of picture pixels for color and single gray background. This is done by solving the fog problem and low-color saturation items, which only assume that small objects have low color saturation. Median filter is used to maintain the less complicated and regular image scale borders. Besides this median of the median filter along the axes, edges as well as angles were retained. Only four criteria, a veil approximation, image restoration, smoothing and tone mapping tunes are used to describe the algorithm. The methodology is regulated by the assumption of the environment, the reconstruction of photographs and the softening and tone-maps. There have been extensive qualitative and quantitative studies.

- D Berman [9]: landscape photographs often have haziness that decreases clarity and contrast. Furthermore each pixel is degraded differently depending on the scene point to the camera. The reason for hazing and attenuation is transmission coefficients. It is not a fix previously oriented, unlike previous methods. It is an assumption that is not local D Berman et al. stressed the decay is not clear. The transmission coefficient is different for different pixels of the image and is controlled. The colors of the hazel free picture have been suggested to be grouped and spread uniformly over the RGB file. These pixels are not local color clusters. Based on their varying propagation factors, these pixels are distributed differently. While the hazy photo represents the color line previously grouped, it's called the hazy line. This restores distance chart and haze free image from haze line replication. The algorithm is linear, faster, deterministic and not necessary for training.

- S Roy et al. [10-13]: In [10], three gamma corrections algorithms, contrast controls, sky masking's and directed flowers have been introduced by scientists. Authors of [11-13] stated that DCP methods and picture statistical analysis should be scientifically evaluated. In essence DCP is a patch-based or prior local one. The scale of the patch was 15x15, omega was 0.95. All dimensions have an important role to play. That's proved. DCP is a valuable algorithm for sky masking. But it is difficult to find the worth of the desired value. It is hand-assessed. The Cuckoo Search Algorithm used to restore this difficulty [11]. The resulting image with CSA very well eliminates sky reflection objects. Improving visibility is a classical problem of Inverse. Haze is always linked to blurring. Both were treated and removed here. Computational complexity is an integral part of any computing task. Computational complexity of qualitative and quantitative analytics for fast deployment has been reduced [13].

IV. Image Formation Physics based Model, Inversion and Noise

Restoration based dehazing basically recovers original scene radiance by an inverse transformation. Well known transformation models are: i) Degradation model and ii) Physics based optical scattering model.

Fig. 2 shows degradation model where f(x) is the original scene radiance, g(x) is the degraded image, h(x) is the degradation function, and n(x) is the additive noise. Then, the linear time invariant system is represented by

$$g(x) = f(x) * h(x) + n(x) \tag{1}$$

Koscheder [1] proposed the physical optical dispersion model in 1924, and the McCartney [2] supported it on the basis of the Mie scattering. This model is now a photography research hotpots. In [3] 1998, this pattern was used to improve turbid air visibility. According to this camera-captured model image, two sections are divided: I direct attenuation of light from scene to camera, and ii) air dispersion to the camera. A blurry, low contrast, and poor visibility were the final image created by the camera. Fig. 3 demonstrates this process.

Considering all the above constrains, atmospheric scattering model can be represented by

$$I(x) = J(x) * t(x) + A(1 - t(x)) \tag{2}$$

Where the first term is degraded image, J(x) represents original scene radiance/ image, t(x) is transmission map, and Atmospheric light. In equation 2, three variables are unknown. Out of these three, two variables, J(x) and t(x) are extremely ill-posed. If t(x) and A could be estimated, then J(x) could be recovered. Therefore, it is evident that good or optimum estimations are the key to restore J(x). This t(x) can be estimated from depth estimation, multiple images, or from some prior.

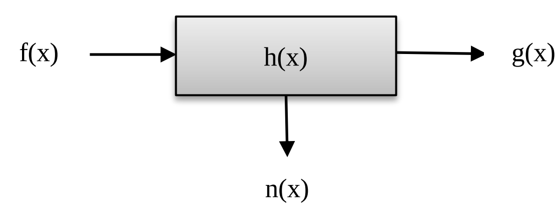

Fig. 2. Image Degradation Model.

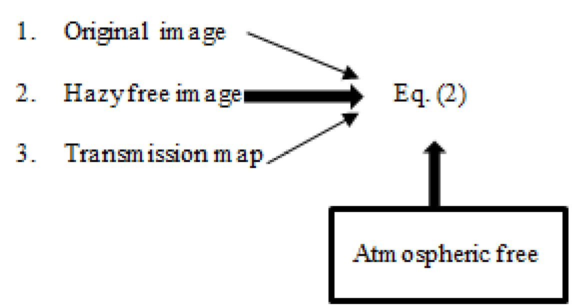

Fig. 3. Image Formation Optical Model.

V. Image Recovery under L0 Norm Regularized (L0Reg) Model

(Positive) scalers to measure length, error, size, distance, etc. depending on the environment is known as Norm. The consistency of the space of a series may be changed by manipulating the option of norm in the infinite dimension. Whereas the convergence of a series is invariant in the case of the final element vector-space. For its efficient use field, however, awareness of different standards is important. For a set of quantities, vectors or matrices in mathematics, the norm reflects the spectrum stands for Common norms: the mean square defect, Euclidean distance, absolute value, Manhattan, p-norm etc.

A. P-Norm (lp Norm)

It is noteworthy here that all Lp norm look alike, but their mathematical as well as application properties shift dramatically. In this work, we are interested in the properties of L0 norm only. L0 norm basically is not a norm, rather cardinality number. This norm has both zeroth root as well as zeroth power. This phenomena makes it problematic to operate. L0 norm recently is in demand due to its sparsity (few number of non-zero elements) , which makes it usable for compress sensing, portability, lastly edge aware smoothing (our main focus). L0 norm optimization is a basically minimization problem and is NP hard problem. Sometimes it is almost unable to solve, and at that point L1 or L2 norm is used as a relaxation. Single image reconstruction is highly challenging, and ill-conditioned in low level vision technique. Main objection of the problem is to estimate robust and accurate kernel for the noisy, blurry image. Here appropriate regularization term or prior estimation is essential to develop sharp images or blur kernel design. Blur kernel design is deeply founded on Bayesian Principal, which encompasses two inference principles: i) Maximum a postrioiri (MAP), ii) Variational Bayes (VB). MAP and VB techniques are sometimes combined sequentially. MAP is exercised more commonly. The reason is: i) intuitive, ii) simple problem formulation, iii) flexible regularisation term, and iv) efficient numerical representation. In practice MAP tracks l0 -norm of various forms to estimate dominant edge where kernel estimation is the main cue, either explicitly or implicitly. It has been experimentally established that l0-norm works far better in blind image de-blurring which will be utilized subsequently in our dehazing algorithm [l0 blind]. L0-norm based image smoothing is a well-known optimization technique which controls globally the number of non-zero gradient to represent prominent structure in a sparsity controlled manner. The special feature of this technique is to sharpen major edges while discarding the unnecessary edges. This trade-off is attainted in an optimization system through L0 gradient minimization [L0-norm Image smoothing]. It is an image editing method, predominantly effective by trade off in optimization framework of L0 gradient minimization sharpening major edges with increasing the steepness of transition while eliminating non prominent, local or noisy information of low-amplitude structures. This is achieved globally control how many non-zero gradients are resulted in to approximate prominent structure in a sparsity-control manner. Unlike other edge-preserving smoothing approaches, our method does not depend on local features, but instead globally locates important edges. It, as a fundamental tool, finds many applications and is particularly beneficial to edge extraction, clip-art JPEG artifact removal, and non-photorealistic effect generation.

B. I-D Smoothing

Main achievement is to get high contrast edges with non-zero gradient without effective geometric structure global smoothing. g is a discrete input function with its smoothed output version f. The concept counts amplitude variations discretely and represented by equation 3.

$$c(f) = \#\{p \mid |f_p - f_{p+1}| \neq 0\} \qquad (3)$$

p and p+1 indicated neighboring samples (pixels) index. $|f_p - f_{p+1}|$ indicated forward gradient w.r.t p . #{} indicates count-ing w.r.t p and it is not equal to zero that satisfies L0-norm gradient. Thus $c(f)$ counts only non-zero gradient, not the change in contrast and it is the essence of the algorithm. Now, $c(f)$ is associated with a general constraint of ‘f’ , output , to be structurally similar to that of ‘g’, input. To implement this a cost function or objective function is designed as equation

$$\min_f \sum_p (f_p - g_p)^2 \ \ s.t. \quad c(f) = k \qquad (4)$$

Where, c(f)=k indicates non-zero gradients from the result. It has been found by minimizing eq. 4 , k =6, through extensive search. The result is better than BLF, LCIS, WLMS, and TVS. Larger k produces fine approximation. But, in case of 2D images with different resolution, the value of k is in the range of ten to thousands. To get the structural resemblance between input and output image with non-zero gradient equation 4 has to be rewritten as

$$\min_f \sum_p (f_p - g_p)^2 + \lambda.\ c(f) \qquad (5)$$

Here, λ is weight or controlling parameter also known as Lagrange Multiplier whose primary work is to balance between c(f) and rest of the equation , so that optimal smoothing can be achieved.

C. 2-D Representation

In 2D Image format, the above mathematical formulation will be represented by I as input and S as output. The gradient for each pixel p is represented as the colour difference between neighboring pixels along x, and y directions.

$$\nabla S_p = (\partial_p S_p, \partial_y S_p)^T \qquad (6)$$

The gradient in this context is given by

$$C(S) = \#\{p \mid |\partial_x S_p| + |\partial_y S_p| \neq 0\} \qquad (7)$$

The above eq. (7) counts non-zero gradient p whose magnitude is $|\partial_x S_p| + |\partial_y S_p|$. Output image S is computed or estimated by solving the objective function below:

$$\min_f \sum_p (S_p - I_p)^2 + \lambda.\ C(S) \qquad (8)$$

For colour image $|S_p|$ is the sum of three channel RGB and the term, $\sum(S - I)^2$, is responsibility for image structure similarity.

D. Solver

Equation 8 involves a separate C(S) test. Due to two opposite criteria, one of them differentiating between two neighboring pixels and the other counting non null pixels (global statistical discontinuity), the above definition is difficult to resolve. There is no suitable classical optimizer such as a decent gradient or discrete optimizer here. Half quadratic fractionation was instead implemented, an alternative approach, in which an auxiliary variable was assumed to expand original conditions and update them on an iterative basis. The stated problem has already been noticed in nature and the regulation problem with L0-Norm is essentially unworkable. Therefore, here an approximation has to be performed to make the problem tractable without losing salient structure of the original image rather strengthening the image. Two auxiliary variables h_p and v_p have been introduced corresponding to $\partial_x S_p and\, \partial_y S_p$ and respectively. Thus, objective function turns out as

$$\min_{s,h,v}\{\sum_p (S_p - I_p)^2 + \lambda\, C(h,v) + \beta((\partial_p S_p - h_v)^2)\} \quad (9)$$

Here, $C(S) = \#\{p||\partial_x S_p| + |\partial_y S_p| \neq 0\}$ and β is an automatic adaptive parameter which tunes the similarity between two variables (h,v) and their corresponding gradients. As β keeps on increasing, eq (9) converges to eq (8). Eq (9) can be solved by minimizing (h,v) and S one by one in a iterative manner.

E. Sub Problem 1: Computing S

From equation (9) it is evident that to estimate S is to minimize the expression without the term that has no S part and is given below

$$\{\sum_p (S_p - I_p)^2 + \beta((\partial_x S_p - h_p)^2) + (\partial_y S_p - v_p)^2)\} \quad (10)$$

The eq. (10) is quadratic, therefore has global minima by gradient decent. Again, by fast Fourier transform for speeding up with diagonal derivative operator this can be written as

$$S = \mathcal{F}^{-1}\left(\frac{\mathcal{F}(I)+\beta(\mathcal{F}(\partial_x)^*\mathcal{F}(h)-\mathcal{F}(\partial_y)^*\mathcal{F}(v))}{\mathcal{F}(1)+\beta(\mathcal{F}(\partial_x)^*\mathcal{F}(\partial_x)-\mathcal{F}(\partial_y)^*\mathcal{F}(\partial_y))}\right) \quad (11)$$

Where F represents FFT operator and F ()*is the complex conjugate. F(1) denotes FFT of delta function. All the normal mathematical operators are component wise operations accordingly. Lastly FFT operation is easier and faster than its spatial domain when large size matrix of image inversion involved.

F. Sub Problem 2: Computing (h,v)

Objective function for minimization (h,v) is derived from equation (9) as

$$\min_{h,v}\{\sum_p (\partial_x S_p - h_p)^2 + (\partial_y S_p - v_p)^2 + \frac{\lambda}{\beta} C(h,v) \quad (12)$$

In the above equation C(h,v) produces non-zero gradient at |h|+|v|. The equation is seemingly sophisticated and complex, but converges quickly due to its spatial processing with individual estimation of h_p , and v_p. Therefore, from equation it is clear that by splitting the equations (9-12) intractable equation becomes tractable even fast. This is the main benefit of this scheme. Thus equation (12) can be equivalently rewritten as

$$\sum_p \min_{h_p, v_p} \{(h_p - \partial_x S_p)^2 + \left(v_p - \partial_y S_p\right)^2 + \frac{\lambda}{\beta} H\left(|h_p| + |v_p|\right)\}$$

In the above equation (13), ($|hp|$ + $|vp|$) is a binary function with

$$H(|h_p| + |v_p|) = f(x) = \begin{cases} 1, |h_p| + |v_p| \neq 0 \\ 0, \ otherwise \end{cases} \quad (14)$$

Now, equation (13) is rewritten w.r.t p as

$$E_p = \{(h_p - \partial_x S_p)^2 + \left(v_p - \partial_y S_p\right)^2 + \frac{\lambda}{\beta} H\left(|h_p| + |v_p|\right)\} \quad (15)$$

Above equation (15) touches its minima under the condition as

$$(h_p, v_p) = f(x) = \begin{cases} (0.0), \ (\partial_x S_p)^2 + (\partial_y S_p)^2 \\ (\partial_x S_p, \partial_y S_p), otherwise \end{cases} \quad (16)$$

The technique describes above is summed up and presented as algorithm below:

Algorithm I L0 gradient minimization, which can regulate globally how many non-zero gradients contribute to a sparsely regulated approach to the popular framework. In comparison to other smoothing methods to maintaining the edge, our process relies not on local characteristics, but on essential edges worldwide. As an essential tool, it has many uses and is especially useful to strip outlines, erase JPEG artefact clip-art and produce non-photorealistic results. To order to identify distinct but weak edges and rebuild the structure from hazes, a scarce gradient is used with L0-norm. This fundamental is applicable in numerous ways. L0 -norm minimization is a NP-Hard, non-convex problem [14, 15, 17].

VI. Application of L0Reg in Image Formation Model

Image formation model output consists intrinsically and extrinsically of noise. Extrinsic noise is the result of an inherent acquisition system that makes the output image profound and hazy and intricate noise. This paper highlights the need to extract meaning from the distorted file, which makes it easier to relay and eventually creates a hazel-free image. By L0 optimization, the depth map is restored. As already stated, a sparsely regulated method of L0 gradient minimization between non-zero gradient numbers is necessary to approximate prominent structure. Equation (2) is the concept of image loss based on optical mechanics used in this paper [1, 2]. Equation transmission (18) was predicted. The pictures, primary photos, transmittance and ambient light shall be I(x), J(x), t(x), and A. β, d are extinction coefficient and distance, respectively.

$$t = e^{-\beta d} \quad (17)$$

Each pixel is distorted by both additive and multiple noise during transfer from the initial scene point to the acquisition stage. The sound transforms the pixel color, contrast, luminosity and sharpness, rendering the resultant image white and almost invisible. It is difficult to deal with the problem when the tool is a single image. Therefore, the depth map [12,13] is taken into account by a total of three RGB channels, and the optimization of the L0 gradient is performed with this non-noiseless clear communication.

$$I_{cmin} = (\min_{c \in \{r,g,b\}}(I^c(x)) \quad (18)$$

I^c and I_{cmin} indicate individual channel of RGB image and minimum of three channels I^c respectively. A raw depth chart for the retrieval of hazardless artifacts can now be utilized as the noise in I_{cmin} minimal strength channel and quickly noise is made free or smoothed by the L0- Gradient minimizing process of the equation (16).

$$I_{cminL0} = L0(I_{cmin}) \quad (19)$$

Noise-free minimum pressure canal or simplified depth chart is shown in Equation (19). This is the normalization of this screen. Complimenting this method, the L0-Gradient Low Intensity Channel with global non-zero gradient modulation would result in a large image structure and reduced computational complexity. It's a big benefit. In the transmission estimate t(x), this maximum intensity channel is used. This transfer is seriously ill. The minimization of L0-Gradient produces a seamless and high-quality brass-free image without missing a significant image structure. Depth map is more reliable by minimum patch estimates but less common because of its machine cost [7] for easy usage. This theoretical concept is simple and easy to implement computationally. This approximation can be useful for easy implementation without hindering visibility and is defined by equation (20).

$$t_{new}(x) = 1 - kI_{cminL0} \tag{20}$$

t_{new} ,k are refined transmission and a proportionality constant for aerial perspective respectively. The value of k is between 0 to 1. Zero indicates clear visibility like clear day scene, whereas one indicates absolutely no visibility like thick fog. The concept of k, haziness factor have be discussed in detail [7, 12, 13]. Transmission map suggested by equation (20), scene radiance now can be evaluated as

$$J(x) = \frac{I(x)-A}{\max(t(x),t_0)} + A \tag{21}$$

Here, a restriction is imposed by introducing t_0 a lower bound of transmission in such a way that even in dense haze a small amount of transmission will be there. Typical value of t_0 is 0.1. Eq. (21) shows a linear equation of computational complexity O(n).

VII. Importance of Quality Assessment in Image[4]

An essential step in image processing is the image quality assessment (IQA). IQA requires accuracy and picture readability, which is split into (i) subjective evaluation and (ii) quantitative evaluation.

A. Subjective Assessment

The observer's visual vision is significant here. There are few guidelines for determining algorithm performance through visual picture presentation. The scale is separated into five degrees. Table I contains a set of opinions where more opinions from different people support the accuracy of the algorithm. This choice can be rendered by image processing experts or rising consumers.

B. Objective Assessment

Here, image is estimated with respect to objective criteria. Three major aspects are there in image: i) full reference, ii) reduced-reference, and iii) no-reference. Specially dehazing is under no-reference criteria, as it is very difficult to get clear image of the same scene. Therefore, no-reference, also known as single image, dehazing is difficult to design algorithm as well as to evaluate. The evaluation is splitted into two: i) ordinary method, and ii) special method.

1) Ordinary IQA: There are several IQA accessible for visual dehazing purposes, some of which are discussed here. Standard Deviation (SD): This metric shows the amount of dispersion from the mean value of the image and is a measure of the contrast of the subject under consideration. Lower interest is perceived. Mean / Average Gradient (MD): This parameter shows the amount of detail of the file. Information Entropy (IE): is a measure of the energy of the image. High entropy value implies more detail. Low value implies material loss. Mean square error (MSE): Metric is commonly used only to calculate the discrepancy between two images. Low value is desired and shows the proximity between two images. Structural similarity SSIM: is a measure that seeks similarities between two images and has a meaning of [0 1]. Low value means less comparable, while high value implies closeness between the two pictures.

2) Ordinary IQA: There are few IQAs which can only be used to dehaze the graphic. The details was elaborated: i. Visible edge dependent technique: Hautiere et al. proposed a blind contrast improvement argument based on an ambient luminance and illumination degree model initially applied to lighting engineering. This indicates three measures, there are very few IQAs that can be used for face dehazing only. The details was elaborated: (i) Visible edge dependent method: Hautiere et al. proposed a blind contrast enhancement approach based on an ambient luminance and illumination degree model originally applied to lighting engineering. It displays three metrics. Check for contrast improvement details between both the hazy and haze-free images. (ii) Color distortion centered technique: color distortion is an obvious issue in the dahazing method. Li et al. introspected color shift and halo / ring influence and developed color histogram index, histogram similarity and color restoration coefficient. This methodology gives a fair estimation of the degree of color revival. But the method suffers from the complexity and richness of color. It's iii. Contrast-naturalness-colorfulness (CNC) method: Guo et al. proposed a CNC evaluation methodology to determine contrast, color naturalness and colorfulness. The product of this approach is similar to the visual perception of the human eye. Also, the methodology influences the sophistication and the use of parameters. Yeah, iv. Machine learning-based technique Chen et al. stated IQA in terms of classification issues and presented a SVM rank with a performance indicator for foggy, undersea, and low-light images w.r.t recuperated clean images. It has established this scheme as the best NR-IQA technique for image dehazing. However, it is complex and the same classification criteria do not meet all types of images.

TABLE. I. SUBJECTIVE ASSESSMENT PERFORMANCE METRIC

Score	Assessment grade	Quality criteria
1	worst	The worse in the group
2	Worse	Worse than average
3	Average	Average in the group
4	Beter	Better than average
5	Best	the best in the group

VIII. Results

It was already mentioned that subjective and objective evaluations have such a crucial role to play in validating the performance and appropriateness of the algorithm. Many state-of-the-art algorithms have been designed to perform an inspection of quantity and quality together with the suggested one.

A. Subjective Evaluation of Various Methods

Performance of images with qualitative subjective judgment is a really good visual viewpoint attempt. As can be seen, all the accessibility of our work is better, the images are bright, the color fidelity acceptable, the artifact free with extremely low complexity.

B. Objective Analysis of Various Methods

As reported in contrast to visual analysis, objective analysis was carried out using eight different development criteria based on statistical statistics for images PSNR, SSIM, e, r, Entropy, NIQE, BRISQUE [19]. It provides details of the parameters in Table II. This metrics are used on four varying outdoor images with various techniques and are tabulated in Table III. The actual assessment report is useful. It is evident from Table III that each approach has its own perspective. While the estimation of the efficiency of haze removal is a complex problem difficult to address, taking into consideration both the findings of mathematical statistics and the visual effects, the fact that the proposed method is suitable for haze removal can support this.

IX. Time Complexity

The most important requirement for any algorithm is performance, how much time and energy is being used to complete a task in terms of seconds and megabytes, respectively. Nonetheless, this is not a subjective evaluation owing to its reliance on the computer system and the data collection used [16]. Computational complexity of the L0-Norm Gradient is O(n) as shown in Algorithm I and that of the proposed method in Suggested Algorithm II is O(n) as well. Overall, however, the suggested methodology retains the computational complexity of O(n) which is significant for rapid activity, such as large-scale real-time image processing. This is not to suggest that the current approach is the highest, but effective with low computational complexity.

X. Application of L0-Gradient Dehazing on different Degraded Images [dataset FRIDA]

Images with different degraded form like underwater, rain, close object, nighttime, etc. have been examined and found remarkable results. Therefore, this can be concluded that the proposed approach is equally applicable for any kind of degraded images as well. (Fig. 4: Application of L0-Norm Dehazing on different degraded images.)

Images with various deteriorated forms such as underwater, fog, near object, nighttime, etc. have been analyzed and impressive findings have been identified.It can therefore be inferred that the proposed solution is equally applicable to any form of degraded image. (Fig. 4: Implementation of L0-Norm Dehazing to distinct deteriorated images.)

Fig. 4. Shows Application of L0-Norm Dehazing on different Degraded Images.

XI. Discussion, Shortcoming and Future Scope

The above described approach has been experimented with the natural haze image dataset of K He and FRIDA. Based on the high demand for dehazing, images of day-time, night-time, underwater, rainy, and nearby objects of different types of obscure scene with severe deterioration have been examined as far as possible. So, through studying and evaluating the resulting pictures, it can be concluded that all forms of ambiguous images have also regained their exposure with this algorithm. The state-of-the-art studies on dehazing have been reviewed in this paper. In addition, L0-gradient minimization of image smoothing was studied in combination with H Kosmedier Image Formation Physical System to solve the dehazing issue as L0 smoothing approximates better results with higher false discovery rate (FDR). Depth map has been derived from a total of 3-RGB channels with a L0-gradient pixel smoothing operator to generate a smoothed edge reconstruction in a sparsity-controlled manner. Prediction of a depth chart has been found to be a difficult task. As a consequence, a powerful-principled and well-designed algorithm was introduced along with discreet spatial adjustments that hold prominent and conspicuous edges to form significant structures and discard low amplitude structures as noise. That, in effect, has established an ideal transmission that contributes to the final result of an optimum clear image. This method applies equally to the Dehazing Gray Image. Halo effect during dehazing is a common issue sometimes found in dehazing. The use of this halo effect technique is restricted. In Our method, selecting the parameter lamda is a trade-off between over-sharpening and over-smoothing. Careful use of lama is therefore a fantastic decision-making tool and relies on the specific picture scenario. It has to be kept independent of the particular situation. In the future, this approach can be extended with some alteration to other demonizing and de-blurring issues. Another important field of use is the calculation of depth for textual segmentation, object detection in a perception challenge where the ground reality dataset is inaccessible. Minimizing time variability is a big drawback for any real-time program. Here, this algorithm also faces this challenge. There is significant potential for the improvement of good image performance in the future with the progress in camera technology and computer processing. MATLAB 2017b has been used as tools in Windows 10 settings.

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APPENDICES

TABLE. II.

Metric	Full Form	Type	Desired Value
PSNR	Peak Signal-to-Noise Ratio	Full Reference Image Quality Metric	High
SSIM	Structural Similarity Index	Full Reference Image Quality Metric	High(0-1)
e	Percent of Newly Visible Edge	Full Reference Image Quality Metric	High
σ	Normalized Newly Found Saturated Pixels	Full Reference Image Quality Metric	High
r	Geometric Mean of the ratio of Visibility Level	Full Reference Image Quality Metric	High
Entropy	Energy (Intensity) of the pixels	No Reference Image Quality Metric	High
NIQE	Naturalness Image Quality Evaluator	No Reference Image Quality Metric	Low
BRISQUE	Blind / No Reference Image Special Quality Evaluator	No Reference Image Quality Metric	Low

TABLE. III.

Metric	Fig. 1	Fig. 2	Fig. 3	Fig. 4
Entropy of original image	7.1535	7.4330	7.4373	7.4436
	7.15335	7.4330	7.4373	7.4436
L0_Dehaze				
PSNR	9.6203	11.9366	12.0643	13.6133
SSIM	0.4118	0.2340	0.5862	0.6431
Antropy of Restored Image	6.4997	7.7436	7.3314	7.8284
NIQE	18.8815	18.8837	18.8773	18.8809
BRISQUE	21.8087	43.6497	24.3925	31.4020
e	-0.0162	-0.0346	0.4580	-0.0484
σ	4.9600	2.56	8.2933	1.1467
r	0.9051	2.5208	1.3836	1.4904
Fattal				
PSNR	16.2893	22.5839	17.1703	19.9720
SSIM	0.8686	0.9146	0.8583	0.9451
Entropy Restored	7.1167	7.7226	7.6079	7.6121
NIQE	18.8814	18.8808	18.8761	18.8812
BRISQUE	15.7537	24.3711	42.7872	46.2568
e	-0.0153	-0.1632	0.0572	0.0264
σ	0.0133	0.4800	0	0.0667
r	1.1740	1.4430	1.1750	1.2636

ALGORITHM I

Algorithm:1	**L0 gradient minimization**	**Complexity**
Input:	Image I, smoothing weight λ, parameter β0 , βmax and rate k	
Initialization:	S←I, β←β0, i←0	O(n)
Repeat:	With $S^{(i)}$, solve for $hp^{(i)}$ and $vp^{(i)}$ in eq(16)	
	With $hp^{(i))}$ and $vp^{(i)}$, solver for $S^{(i+1)}$ with eq(11)	
	β←kβ, i++.	
Until:	β ≥ βmax	
Output:	Result Image S	

ALGORITHM II

Algorithm 2	**Input Hazy Image**	**Computational Com- plexity**
Step I	Average of minimum of three channels as Imin	O(n)
Step II	Average of maximum value of three channels as Imax	O(n)
Step III	Contrast value=Imax –Imin	O(n)
Step IV	Haziness factor, k =Imin / Imax	O(n)
Step V	Airlight Estimation	O(n)
Step VI	Estimation of minimum intensity channel	O(n)
Step VII	Refinement / noise removal of minimum intensity channel by L0-Norm Gradient	O(n) [15]
Step VIII	Transmission Estimation	O(n)
Step IX	Recovery of Dehazed image with image degradation model	O(n)