A Survey on Techniques for Efficient Image Dehazing

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Abstract-* Haze is an atmospheric phenomenon that significantly degrades the visibility of outdoor scenes. This is mainly due to the atmospheric particles that absorb and scatter light. This examination introduces various images dehazing approach based on literature survey that enhances the visibility of such degraded images. The atmosphere in a scene incorporates a few kinds of pressurized canned products such as haze, dust, or fog. When camera men capture a scene photograph of a landscape, often thick aerosols scatter light transport from the scene to the camera, resulting in a hazy photograph. It diminishes the perceivability of the scenes and brings down the unwavering quality of outside observation frameworks; it degrade the clarity of the satellite images; it also decreases the contrast and changes the colors of daily photos, which is an annoying problem to photographers. Therefore, removing haze from images is an important and widely demanded topic in computer vision and computer graphics areas. This examination reported an extensive survey of literature on a patch quality comparator for single image dehazing.

***Keywords-* Haze removal, image dehazing, contrast enhancement, Patch Quality Comparator, Convolutional Neural Network.**

I. INTRODUCTION

An image processing technique that removes a layer of haze and compensates the attenuated energy is known as dehazing. It can be applied to many outdoor imaging applications such as self-driving vehicles, surveillance, and satellite imaging. The general dehazing algorithm consists of two main processes. First need to approximate haze initially by utilizing available haze clues based on a certain assumption on natural image statistics, such as a dark channel prior. In this stage, most of dehazing algorithms tend to produce an incomplete transmission map from the hazy image. Once obtain rough approximation of haze, there is a need to propagate the sparse information to the entire scene to reconstruct a dense transmittance map, which yields a haze-free image.

Difficulty of dehazing arises from the existence of ambiguity due to the lack of the scene information. First, the initial assumption on image statistics on natural colors in particular is insufficient to cover the wide diversity of natural scenes in the real world, resulting in incomplete haze estimation. No universal image statistics on natural colors can handle the dehazing problem. Moreover, most of propagation algorithms with a common grid random field often suffer from haze-isolation artifacts. The amount of haze in the atmosphere at each pixel is determined by its depth. If there is an abrupt change in scene depth, the grid random field cannot regularize a transmission map with sharp-edge discontinuity due to wrong propagation. In order to handle abrupt changes of haze density, there is a need scene depth information, even though it is unavailable in single-image dehazing.

Fig.1.1 Haze in image, Left: hazy image. Right: Original image.

The main challenge lies in the ambiguity of the problem. Haze attenuates the light reflected from the scenes, and further blends it with some additive light in the atmosphere. The target of haze removal is to recover the reflected light (i.e., the scene colors) from the blended light. This problem is mathematically ambiguous: there are an infinite number of solutions given the blended light. How to determine which solution is true. There is a need to answer this question in haze removal.

Ambiguity is a common challenge for many computer vision problems. In terms of mathematics, ambiguity is because the number of equations is smaller than the number of unknowns. The methods in computer vision to solve the ambiguity can roughly categorized into two strategies. The first one is to acquire more known variables, e.g., some haze removal algorithms capture multiple images of the same scene under different settings (like polarizers). But it is not easy to obtain extra images in practice. The second strategy is to impose extra constraints using some knowledge or assumptions.

known beforehand, namely, some “priors”. This way is more practical since it requires as few as only one image. To this end, focus on single image haze removal in this examination. The key is to find a suitable prior.

Haze Imaging Model

The haze imaging equation is given by

$$I(x) = J(x)t(x) + A\big(1 - t(x)\big) \ldots\ldots\ldots\ldots\ldots\ldots\ldots (1.1)$$

An example of the haze imaging equation is given in Eq. 1.1. The variables are explained in the following: x = (x, y) is a 2D vector representing the coordinates (x, y) of a pixel’s position in the image.

I represents the hazy image observed. I(x) is a 3D RGB vector of the color at a pixel.

J represents the scene radiance image. J(x) is a 3D RGB vector of the color of the light reflected by the scene point at x. t is a map called transmission or transparency of the haze. • A is the atmospheric light.

II. LEARNING-BASED DEHAZING

One of the most important tasks of computer vision is to represent distinctive local image patches in a way that their representation is invariant under different viewing conditions. This is a crucial step in multiple applications such as structure from motion, image retrieval, object recognition, simultaneous localisation and mapping (SLAM) and tracking. Recent interest in self-driving cars has made this area a very important part of any relevant advancement. The goal of a robust feature descriptor is to represent a specific area of the image on the left in such a way that it can be easily matched with the equivalent area on the right image.

Local feature descriptors should be robust to various transformations, such as blurring, affine projections and illumination changes, while at the same time being efficient to compute, low in memory requirements and fast to match. Influential early work in this area focused on real-valued feature vectors extracted from distributions of image characteristics such as gradients and colours. However the computational complexity of estimating distributions using real valued features limits the set of applications where such features could be efficiently employed. In addition, large-scale methods such as searching among billions of examples require descriptors to have smallest memory footprint possible. Recent developments in Deep Learning have greatly advanced the performance of these state-of-the-art visual recognition systems to the extent of sweeping aside the hand crafted models such as BoW. Nowadays a lot of products in the industry have benefited from the past years of research in Deep Learning.

Learning algorithms are widely used in computer vision applications. Before considering image related tasks, are going to have a brief look at basics of machine learning. Machine learning has emerged as a useful tool for modelling problems that are otherwise difficult to formulate exactly. Classical computer programs are explicitly programmed by hand to perform a task. With machine learning, some portion of the human contribution is replaced by a learning algorithm. As availability of computational capacity and data has increased, machine learning has become more and more practical over the years, to the point of being almost ubiquitous.

Neural networks were originally called artificial neural networks, because they were developed to mimic the neural function of the human brain. Pioneering research includes the threshold logic unit by Warren McCulloch and Walter Pitts in 1943 and the perceptron by Frank Rosenblatt in 1957.

Even though the inspiration from biology is apparent, it would be misleading to overemphasize the connection between artificial neurons and biological neurons or neuroscience. The human brain contains approximately 100 billion neurons operating in parallel. Artificial neurons are mathematical functions implemented on more-or-less serial computers. Research into neural networks is mostly guided by developments in engineering and mathematics rather than biology.

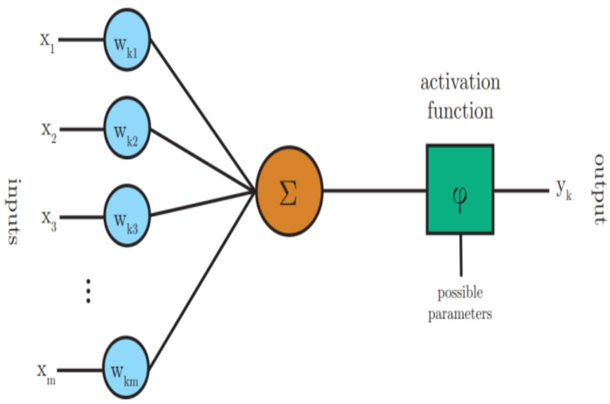

Fig. 2.1 An artificial neuron.

An artificial neuron based on the McCulloch-Pitts model is shown in Figure 2.1. The neuron k receives m input parameters x_j . The neuron also has m weight parameters w_{kj} . The weight parameters often include a bias term that has a matching dummy input with a fixed value of 1. The inputs and weights are linearly combined and summed. The sum is then fed to an activation function ϕ that produces the output yk of the neuron.

III. LITERATURE REVIEW

SR NO.	TITLE	AUTHORS	YEAR	APPROACH
1	Learning a Patch Quality Comparator for Single Image Dehazing,	S. Santra, R. Mondal and B. Chanda,	2018	A Method that dehazes a given image by comparing various output patches with the original hazy version and then choosing the best one
2	Learning-based local-patch resolution reconstruction of iris smart-phone images,	F. Alonso-Fernandez, R. A. Farrugia and J. Bigun,	2017	Evaluated two trained image reconstruction algorithms in the context of smart-phone biometrics based on the use of coupled dictionaries to learn
3	Learning-based single image dehazing via genetic programming	Chulwoo Lee and L. Shao	2016	A genetic programming (GP)-based framework to learn the effective feature representation for image dehazing
4	A Fast Training Example Searching Algorithm for Data-Driven Dehazing	X. Tang, X. Fan, Y. Duan and Z. Luo,	2016	Gaussian Process Regression (GPR) to learn the relationship between the hazy image and the transmission map
5	A Patch-Structure Representation Method for Quality Assessment of Contrast Changed Images	S. Wang, K. Ma, H. Yeganeh, Z. Wang and W. Lin	2015	A novel local patch-based objective quality assessment method using an adaptive representation of local patch structure
6	Blind Image Quality Assessment for Stereoscopic Images Using Binocular Guided Quality Lookup and Visual Codebook	F. Shao, W. Lin, S. Wang, G. Jiang and M. Yu	2015	A new blind image quality assessment for stereoscopic images by using binocular guided quality lookup and visual codebook.
7	Haze removal without transmission map refinement based on dual dark channels	C. Hsieh, Y. Lin and C. Chang	2014	A dehazing algorithm with dual dark channels where the soft matting to refine the transmission map is avoided and the atmospheric light is estimated directly from a dark channel

S. Santra, R. Mondal and B. Chanda [1] In bad weather conditions such as fog and haze, the particles present in the atmosphere scatter incident light in different directions. As a result, the image taken under these conditions suffers from reduced visibility and lack of contrast, and as a result, it appears colorless. An image dehazing method tries to recover a haze-free portrayal of the given hazy image. In this investigation, a method that dehazes a given image by comparing various output patches with the original hazy version and then choosing the best one is reported. The comparison is performed by our proposed dehazed patch quality comparator based on the convolutional neural network. To select the best dehazed patch, employ binary search. Quantitative and qualitative evaluations show that our method achieves good results in most of the cases, and are, on an average, comparable with the state-of-the-art methods.

F. Alonso-Fernandez, R. A. Farrugia and J. Bigun [2] Application of ocular biometrics in mobile and at a distance environments still has several open challenges, with the lack quality and resolution being an evident issue that can severely affects performance. In this examination, evaluate two trained image reconstruction algorithms in the context of smart-phone biometrics. They are based on the use of coupled dictionaries to learn the mapping relations between low and high resolution images. In addition, reconstruction is made in local overlapped image patches, where up-scaling functions are modelled separately for each patch, allowing to better preserve local details. The experimental setup is complemented with a database of 560 images captured with two different smart-phones, and two iris comparators employed for verification experiments. Experiment show that the trained approaches are substantially superior to bilinear or bicubic interpolations at very low resolutions (images of 13×13 pixels). Under such challenging conditions, an EER of ~7% can be achieved using individual comparators, which is further pushed down to 4-6% after the fusion of the two systems.

Chulwoo Lee and L. Shao [3] A genetic programming (GP)-based framework to learn the effective feature representation for image dehazing is proposed in this work. In GP, an individual program is randomly generated and genetically evolved to achieve the desired goal. To make GP estimate haze in an input image, a set of operators and operands is designed, each of which is a primitive of a GP program. Specifically, provide four basic features as candidates, and also include function operators to construct sophisticated representations of these features. After the entire GP process finishes, obtain a near-optimal compact descriptor for haze estimation. Experimental results demonstrate that the proposed algorithm enhances the visual quality of haze-degraded images both objectively and subjectively.

X. Tang, X. Fan, Y. Duan and Z. Luo, [4] Nowadays learning based approaches have been widely used in image processing and have achieved better results than classical methods. The core of the learning approach is data and the performance of the learning model can be greatly improved by the modality-specific training examples. However, few learning based methods study training example searching to optimize the data driven model. In our work, use Gaussian Process Regression (GPR) to learn the relationship between the hazy image and the transmission map. In order to optimize the learning model, reported a training data searching method which adapts to the GPR model. For the given test examples, first use k-dimensional tree to select training examples neighboring to the inputs. Then, based on the optimized GPR, establish the relationship between hazy features and transmissions, and produce the transmission map of the hazy image for dehazing. Experimental results on the hazy image dataset show the effectiveness of the proposed method compared with the state-of-the-art dehazing methods.

S. Wang, K. Ma, H. Yeganeh, Z. Wang and W. Lin, [5] Contrast is a fundamental attribute of images that plays an important role in human visual perception of image quality. With numerous approaches proposed to enhance image contrast, much less work has been dedicated to automatic quality assessment of contrast changed images. Existing approaches rely on global statistics to estimate contrast quality. Here propose a novel local patch-based objective quality assessment method using an adaptive representation of local patch structure, which allows us to decompose any image patch into its mean intensity, signal strength and signal structure components and then evaluate their perceptual distortions in different ways. A unique feature that differentiates the proposed method from previous contrast quality models is the capability to produce a local contrast quality map, which predicts local quality variations over space and may be employed to guide contrast enhancement algorithms. Validations based on four publicly available databases show that the proposed patch-based contrast quality index (PCQI) method provides accurate predictions on the human perception of contrast variations.

F. Shao, W. Lin, S. Wang, G. Jiang and M. Yu,[6] The field of assessing three-dimensional (3-D) visual experience is challenging. In this examination, propose a new blind image quality assessment for stereoscopic images by using binocular guided quality lookup and visual codebook. To be more specific, in the training stage, construct phase-tuned quality lookup (PTQL) and phase-tuned visual codebook (PTVC) from the binocular energy responses based on stimuli from different spatial frequencies, orientations, and phase shifts. In the test stage, blind quality pooling can be easily achieved by searching the PTQL and PTVC, and the quality score is obtained by averaging the largest values of all patch's quality. Experimental results on three 3-D image quality assessment databases demonstrate that in comparison with the most related existing methods, the devised algorithm achieves high consistency alignment with subjective assessment and low-complexity pooling.

C. Hsieh, Y. Lin and C. Chang,[7] Single image haze removal has been a challenge in the field of image processing. In, a haze removal scheme based on dark channel prior (DCP) is presented and is getting popular because of its satisfactory performance for most of cases. However, it is known that the scheme proposed in suffers from two problems: high computational cost and over-exposure when a bright area shown in images. This examination proposes a dehazing algorithm with dual dark channels where the soft matting to refine the transmission map is avoided and the atmospheric light is estimated directly from a dark channel. The objective of proposed dehazing algorithm (PDA) is to alleviate or remove the two problems found. Several examples are given to verify the PDA and to compare it with the DCP scheme the simulation results show that the PDA is about 2.5 times, on average, faster than the DCP since the soft matting is avoided. Similar visual quality to the DCP is found in the PDA which is of better color situation and without over-exposure problem as in the DCP scheme.

IV. PROBLEM STATEMENT

Recorded color images taken in bad environments exhibit problems such as low visibility, reduced contrast and generally bad"quality". For this reason, many methods known as dehazing methods have been designed to improve the perceived image quality in order to be used later in Computer Vision applications, which require images of high quality. Unlike computational photography, image usability and fidelity may be promoted over preference in computer vision. Amongst these two aspects, Often, the images of outdoor scenes are degraded by bad weather conditions. In such cases, atmospheric phenomena like haze and fog degrade significantly the visibility of the captured scene. Since the aerosol is misted by additional particles, the reflected light is scattered and as a result, distant objects and parts of the scene are less visible, which is characterized by reduced contrast and faded colors. Restoration of images taken in these specific conditions has caught increasing attention in the last years. This task is important in several outdoor applications such as remote sensing, intelligent vehicles, object recognition and surveillance. A more challenging problem is when only a single degraded image is available. Prior work reported an image dehazing method that tries to estimate transmittance in each patch by comparing the dehazed version with the input hazy one. The output greatly improves with correct environmental illumination. Still there is a requirement of accurate estimation of environmental illumination for both day and night time cases.

V. CONCLUSION

This examination presents various extensive literature surveys on image dehazing based on learning approaches. In this examination recent approaches used for image dehazing are revived and discusses based on their literature. Since airlight is energy scattered in air, airlight tends to be locally smooth in a scene, i.e., local airlight remains constant in a similar depth. In contrast, the original radiance in a scene tend to vary significantly, naturally showing a variety of colors. When isolate the scene radiance into a small patch in an image, the variation of scene radiances within a patch tends to decrease significantly to form a cluster with a similar color vector, assuming that the real world scene is a set of small planar surfaces of different colors. Learning-based approaches are utilized to mitigate the effect of dehazing problem using a trained prior knowledge (trained artificial neurons). From training datasets, they attempt to earn a prior on natural image statistics to factorize the haze layer and the scene radiance from the hazy image.

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