A Benchmark for Edge Preserving Image Smoothing

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Abstract—- Image smoothing is a continually evolving and improving criterion in today's world. This is because a noise-free image is required in all situations. A proof-ofconcept prototype has been constructed to visualise the effectiveness of the suggested approach. Despite the fact that multiple algorithms have been proposed, there are a number of roadblocks to its further development. To begin with, most existing algorithms are incapable of handling a wide range of image contents with just one parameter value. Second, assessing the effectiveness of edge-preserving picture smoothing is subjective, and there are no widely accepted datasets to objectively evaluate the various approaches. This benchmark contains an image dataset as well as baseline algorithms capable of providing competitive edge-preserving smoothing.-

Keywords-*Benchmark, Edge-preserving, smoothing, Matlab, Deep CNN*

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I. INTRODUCTION

It is critical to preserve fundamental image features, such as conspicuous edges and outlines, while smoothing minor details in many image analysis and modification applications, such as contour recognition, segmentation techniques, and image stylization. Edge-preserving image smoothing, a fundamental challenge in image processing and low-level computer vision, can help with this. Despite the fact that a variety of algorithms with different design philosophies have been developed, there are three issues that are impeding the advancement of edge preserving image smoothing algorithms. For starters, evaluating the performance of edge Many image analysis and manipulation tasks, such as contour detection, image segmentation, and image stylization, require that major image structures, such as salient edges and contours, be preserved while insignificant details are smoothed. Edge-preserving image smoothing, a fundamental problem in image processing and low-level computer vision, can accomplish this. Despite the fact that a number of algorithms with various design philosophies have been proposed, there are three issues that are impeding the further development of edge preserving image smoothing algorithms. For starters, evaluating the performance of edgepreserving smoothing algorithms is still subjective. At the moment, the most common method is visual inspection by subjects.

The second issue is that edge-preserving smoothing techniques are often compared to one another on very tiny image sets. A frequently used large-scale image database for algorithmevaluation is lacking. While a smoothing method can yield excellent results on some kinds of photos, it might not work well on others. Consequently, a big database for a comprehensive assessment of edge preserving smoothing algorithms is much needed.

Third, since smoothing algorithms frequently contain adjustable parameters, different parameter settings are required for photos with various types of content. To the best of our knowledge, no smoothing algorithms can function reasonably well with a single parameter setting on a variety of image contents.

In this research, we suggest a benchmark for edge-preserving image smoothing in order to

address the aforementioned issues. This benchmark contains baseline models that may produce acceptable edgepreserving smoothing results for a variety of image contents, as well as an image dataset with "ground truth" image smoothing outcomes. 500 training and test photos are included in our image dataset, which also includes images of people, animals, plants, indoor environments, cars, and more. The dataset's ground truth smoothing outcomes.

These reasons support the claim. First, as we discussed earlier, a single state-of-the-art smoothing algorithm is capable of producing high-quality smoothing results over a small range of image contents, especially when its parameters have been fine-tuned. Therefore, a collection of smoothing algorithms can produce high-quality results for a wide range of images.However, the best results for a specific image may need to be selected by a human. Second, because an image has so many pixels, it is difficult and time consuming for humans to annotate pixel-by-pixel smoothing results by hand.

To establish the baseline algorithms used in our benchmark, we use the latest deep neural networks with a large number of parameters (weights). If you have trained a deep neural network to perform well on a smoothing dataset, it will be able to generalize well to different image contents. This is the goal we want to achieve for edge- preserving image smoothing.Also note that deep learning is widely applied to low-level computer vision problems and achieves cutting-edge results. Examples include edge preservation filter reproduction, image denoising, image super-resolution, and JPEG deblocking. We use two existing representative network architectures as our starting points: deep convolutional networks (VDCNN) and deep residual networks.

Section II of this research article concisely narrates the whole overview of the system. In section III, IV, we have narrated the project software in detail. The software we used is a Matlab platform. The working of the hardware part comprises of Raspberry Pi model and the motors. In section V we have shown the outcomes which are the screenshots of different software codes and monitoring system.

II.LITERATURE SURVEY

In this section existing systems are discussed, the existing systems are categorized and defined based on their technology used and application methodologies:

A. C. Tomasi and R. Manduchi, “Bilateral filtering for gray and color images,” in Computer Vision Bilateral filtering smooths images while preserving edges, by means of a nonlinear combination of nearby image values. The method is noniterative, local, and simple. It combines gray levels or colors based on both their geometric closeness and their photometric similarity, and prefers near values to distant values in both domain and range. In contrast with filters that operate on the three bands of a color image separately, a bilateral filter can enforce the perceptual metric underlying the CIE-Lab color space, and smooth colors and preserve edges in a way that is tuned to human perception. Also, in contrast with standard filtering, bilateral filtering produces no phantom colors along edges in color images, and reduces phantom colors where they appear in the original image.

B. P. Perona and J. Malik, “Scale-space and edge detection using anisotropic diffusion.” The scale-space technique introduced by Witkin involves generating coarser resolution images by convolving the original image with a Gaussian kernel. This approach has a major drawback: it is difficult to obtain accurately the locations of the ―semantically meaningful‖ edges at coarse scales. In this paper we suggest a new definition of scale-space, and introduce a class of algorithms that realize it using a diffusion process. The diffusion coefficient is chosen to vary spatially in such a way as to encourage intraregional smoothing in preference to Interreg ion smoothing. It is shown that the ―no new maxima should be generated at coarse scales‖ property of conventional scale space is preserved. As the region boundaries in our approach remain sharp, we obtain a high quality edge detector which successfully exploits global information. Experimental results are shown on a number of images. The algorithm involves elementary, local operations replicated over the image making parallel hardware implementations feasible.

C. R. Fattal, “Edge-avoiding wavelets and their applications,” ACM Transactions on Graphics We

propose a new family of secondgeneration wavelets constructed using a robust dataprediction lifting scheme. The support of these new wavelets is constructed based on the edge content of the image and avoids having pixels from both sides of an edge. Multi-resolution analysis, based on these new edge-avoiding wavelets, shows a better decorrelation of the data compared to common linear translation-invariant multi-resolution analyses. The reduced inter-scale correlation allows us to avoid halo artifacts in band-independent multi-scale processing without taking any special precautions

III. PROPOSED WORK

In our present system the algorithm is developed for edge preserving image smoothing purpose using the application of deep CNN i.e., RESNET-50

Many methods have been proposed for on edgepreserving smoothing, which can be categorized into two groups. The first group is local filter-based approaches, where the filters are designed based on image statistics within a local window. Representative filters include Bilateral Filter, Weighted Median Filter (WMF), Anisotropic Diffusion (AD), and Edgeavoiding Wavelet (EAW) . Rolling Guidance Filter (RGF) applies the weighted filters iteratively, and Tree Filtering utilizes minimum spanning tree to smooth out details while preserving major structure.

However, the local filters have a common limitation in that they often introduce artifacts (such as halos along the edge) because only the local image statistics are used in the filtering, and we cannot explicitly control the statistical properties of the filtered images. The second group is global optimization-based approaches. The smoothed image is obtained by solving a global objective function, which usually involves a data term, constraining the distance between original image and smoothed image, and a regularization term, striving to achieve smoothness.

Figure 1: Sample noisy images from our dataset

Representative methods include Weighted Least Square smoothing (WLS) , L0 smoothing , Fast Global Smoother (FGS) , L1 smoothing and SD filter . Such methods overcome several limitations of local filterbased approaches such as halos and gradient reversals. However, increased computational cost comes with solving the large-scale linear systems.

Edge-Preserving Smoothing: Edge preserving smoothing techniques come in a variety of forms and can be divided into two classes The first category is local filterbased techniques, where the filters are created using local window image statistics. Bilateral Filter,Weighted Median Filter (WMF), Anisotropic Diffusion (AD), and Edgeavoiding Wavelet are examples of filters (EAW). In order to smooth out the details while keeping the main structure, Rolling Guidance Filter (RGF) iteratively applies the weighted filters, and Tree Filtering makes use of the minimal spanning tree. Since only the local image statistics are employed in the filtering and we are unable to directly control the statistical features of the filtered images, the local filters all have the disadvantage that they frequently generate artefacts (such as halos along the edge). The following group of large linear systems

Quantitative Evaluation: Bao et al. applied different edge-preserving filters to the test images in Berkeley Segmentation Dataset (BSDS300) prior to boundary detection. F-measure is used to evaluate the filters' effectiveness in suppressing trivial details and preserving edges. Ham et al. proposed ODS and OIS using the gradient magnitudes of filtered images to measure the effectiveness of filters. However, these evaluation approaches may suffer from the deviation of detected boundaries.

Deep Edge-aware Filter Learning: Xu et al. proposed a method to learn and reproduce individual edgepreserving filters. They used a convolutional neural network to predict

smoothed image gradients and then run an expensive step to reconstruct the smoothed image itself. However, the β parameter in their reconstruction step is not fixed and varies with different filters. Liu et al. proposed a hybrid network by incorporating spatially varying recurrent neural networks (RNN) conditioned on the input image. A deep CNN is used to learn the weight map of the RNN.

RESNET-50 : ResNet-50 is a convolutional neural network that is 50 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database [1]. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals etc.

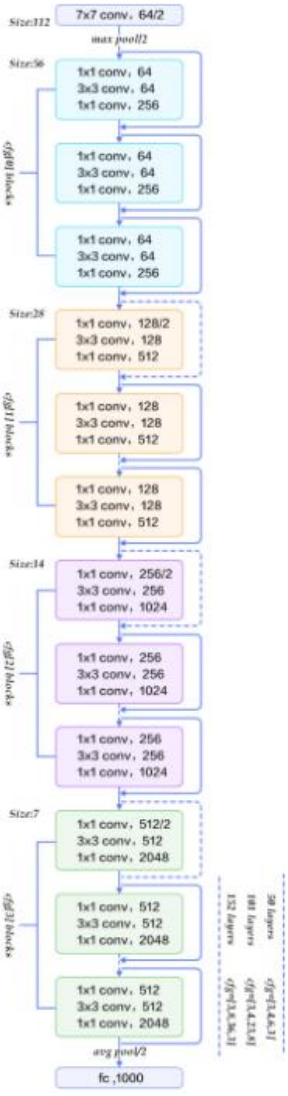


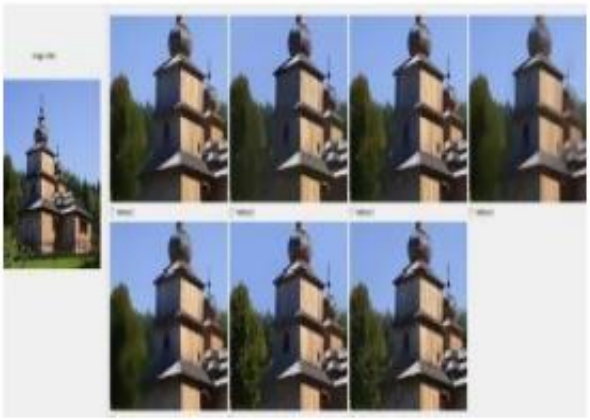
Figure 2: Layers of RESNET50

IV. IMPLEMENTATION

This project is implemented using Matlab software. The algorithm is written based on the comparision of various edge preserving Filters such as Gaussian , Median and using RESNET50

IV.1 DATASET FOR EDGE-PRESERVING SMOOTHING

A major source of our images is the database reported in. This database is composed of a large number of high-quality natural images, which were originally employed for comparing image quality models. Another source of our dataset is the Berkeley Segmentation Dataset (BSDS500) which has been widely used in the computer vision community. We manually chose 500 images of a variety of objects and scenes (humans, animals, plants, indoors, landscape, vehicles, etc.). The selected images in the dataset contain clear structures and visible details which are well suited for evaluating edge preserving smoothing algorithms. Besides, the dataset is balanced among different objects and scenes. The images not suitable for edge-preserving smoothing (e.g., images without clear structures but filled with textured regions) are excluded from our dataset.



(a) Step 1: Choose the best result for each algorithm

(b)Step 2: Choose the best result from algorithms

Figure 3:Snap-shots of two step selection interface

Selection Tool: We chose three state-of-the-art and representative edge preserving algorithms to construct our dataset, including SD filter, L0 smoothing Fast Global Smoother (FGS) , Tree Filtering Weighted Median Filter (WMF) L1 smoothing and Local Laplacian filter (LLF).The selection considerations of these filters are twofold. The first is the representativeness and impact of the work (e.g., high citations). This consideration ensures that the selected filters are state-of-the-arts. The second consideration is the diversity to leverage the merits of different types of filters. Based on these considerations, we selected 4 global methods and 3 local methods. The global filters explicitly formulate the edge-preserving smoothing process as a global optimization problem, while the local filters apply a weighted function depending on the similarity of features within a local window

Parameters		1	2	3	4	5	6	7	8		3	4	5	6	7	8
SD filter	Λ	1	5	15	30	50	70	90	110		15	30	50	70	90	110
$L0$ smoothing	Λ	0.05	0.01	0.02	0.03	0.04	0.05	0.06	0.08		0.02	0.03	0.04	0.05	0.06	0.08
FGS	σc	0.02	0.02	0.025	0.025	0.03	0.03	0.04	0.04		0.025	0.025	0.03	0.03	0.04	0.04
	Λ	400	900	600	900	500	900	400	1200		600	900	500	900	400	1200
Tree Filtering	Σ	0.05	0.05	0.1	0.1	0.2	0.2	0.4	0.4		0.1	0.1	0.2	0.2	0.4	0.4
	σs	8	4	8	4	8	4	8	4		8	4	8	4	8	4
WMF	Σ	10	30	50	70	90	110	130	150		50	70	90	110	130	150
$L1$ smoothing	Λ	10	10	20	20	100	100	200	200		20	20	100	100	200	200
	θ	200	50	200	50	200	50	200	50							
LLF	σr	0.1	0.1	0.2	0.2	0.4	0.4	0.6	0.6							
	α	2	4	2	4	2	4	2	4							

Table 1: Comparison of parameters of various filters

According to the fact that the best smoothing results of different images may come from different algorithms with different parameter settings, we have developed an interactive interface where one can choose the proper edge-preserving smoothing result in two steps: •

Step 1: Given a source image, choose a parameter setting for each algorithm which generates the best smoothing result for that algorithm. •

Step 2: Choose the best one from the best results of the seven algorithms.

We pre-defined eight parameter settings for each algorithm, Selection Protocol As is widely acknowledged, the general criterion for basic edge-preserving smoothing is that the visually salient edges of major structures should be preserved while the trivial details should be removed. Subjects are instructed to select good edge preserving smoothing results from different edge preserving smoothing (EPS) filters with different parameter settings. Since humans could have different perceptual comprehension of trivial details and major structures, they might select different smoothed images as their preferred edge-preserving results To model such perceptual differences .

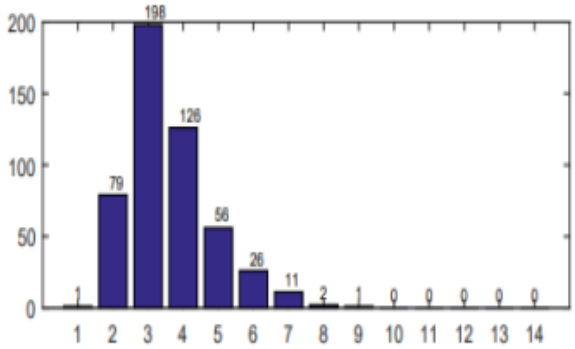


Figure 4: Distribution of the maximum number of repeated choices

V. APPLICATIONS

Smoothing high-contrast details while preserving edges is a useful step in many applications. In this section, we briefly discuss two applications, including tone mapping and contrast enhancement, by applying the trained ResNet model as the edge-preserving smoothing filter.

A. Tone mapping: Tone mapping is a popular technique to map one set of colours to another to reproduce the appearance of a high dynamic range (HDR) image on a low dynamic range (LDR) displayer. The state-of-the-art tone mappers commonly adopt a layer decomposition scheme to decompose the HDR image into low and high-frequency layers and then process them separately. In particular, the low frequency layer is estimated by applying an edge-preserving filter to the original HDR image. The edge preserving property is very important for avoiding halo artifact and achieving naturalness in the tone-mapped images. Thus, a stable and effective edge-preserving filter is highly desirable to improve the tone mapping performance.

B. Contrast enhancement: Contrast enhancement aims to enhance the local contrast of an image that suffers from large illumination variation. Similar to tone mapping, a proper contrast enhancement framework decomposes an image into two components, illumination and reflectance. The estimation of illumination requires a high-performance edge preserving filter

VI. RESULTS

Fig. 5 shows the Edge preserving image smoothing using Matlab software. We have taken the ample images from the dataset of more than 500 images having their own ground truth. The sample images are pixilated according to the requirement of the user. The best algorithm is chosen according to the groundtruth of the image and Edge preserving image smoothing is performed.

(a): Original input image

(b): Smoothed Image using RESNET50

Figure 5: Edge preserving Image Smoothing using RESNET50

VI. CONCLUSION

In this research paper we have presented a new idea to implement A Benchmark For Edge Preserving Image Smoothing using Matlab Software. To advance the state of the art and perform quantitative performance evaluation. This standard contains 500 source photographs and the "groundtruth" behind them. consequences of image smoothing and fundamental understanding models. The baseline models are typical deep models. Architectures for convolutional networks, which We create brand-new loss functions that are excellent for preserving the edges of images. When put to the test, our trained deep networks perform quickly, and their smoothing outcomes exceed cutting-edge smoothing methods both numerically and qualitatively. Networks operate quickly during testing while being smoothed outcomes are superior to modern smoothing both quantitative and qualitative algorithms

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