Evaluation of SD Filter for Multi-Spectral Image De-Noising

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Abstract

Traditional de-noising algorithms using static and dynamic guidance images are already used. The SD Filter leverages both static and dynamic guidance together for many applications. For this project de-noising application is studied. The method uses high detail NIR image as a static guidance for de-noising an visible spectrum RGB image.

To evaluate this method's performance some image metric methods are also studied in this paper.

1. Introduction

Many tasks in image processing requires regularization in order to get good results. Guidance is used to transfer strong structures from one image to another.

Traditional methods use static or dynamic guidance images. Static guidance regularization modulates input image with similarities between two images. It can easily reflect internal properties of the input image. Dynamic guidance regularization on the other hand modulates input image with similarities between neighboring pixels. It can preserve local features better than static guidance regularization.

Robust Image Filtering using Joint Static and Dynamic Guidance[5] paper uses both static and dynamic guidance images together to keep local features and static image structures intact.

Infrared sensors are still developing and thus there are some intrinsic problems with Infrared Imaging(IR). These problems will be dealt with during the project.

TRICLOBS(TRI-band Color Low-light OBServation) Dataset[15] is used for de-noising with multiple spectrum images of the same scene. The dataset includes different civilian or military scenarios executed against a special kind of hardware that records visible, NIR and LWIR spectrum. This database will be used in evaluation part of the method[5].

2. Related Work

Static or dynamic guidance can be implicit or explicit. Implicit regularization stems from a filtering framework.[5]. The input image is filtered using a weight function that depends on the similarity of features in the guidance image. [8]. In this way, the structure of the guidance image is transferred to the input image. The bilateral filter (BF)[16], guided filter (GF) [7], and weighted median filter (WMF) [12] have been successfully adapted to static guidance regularization. Two representative filtering methods using dynamic guidance are iterative nonlocal means (INM) [2] and the rolling-guidance filter (RGF) [6]. They share the same filtering framework, but differ in that INM is for preserving textures during noise reduction, while the RGF aims at removing textures through scale-space filtering. This implicit regularization is simple and easy to implement, but the filtering formalization prevents its wide applicability [5]. For example, it is hard to handle input images where information is sparse, e.g., in image colorization [10]. The local nature of this approach might introduce artifacts, e.g., halos and gradient reversal [7]. Accordingly, implicit regularization has been applied in a highly controlled condition, and usually employed as a pre- and/or post-processing for further applications [9, 12]. An alternative approach is to explicitly encode the regularization process into an objective functional, while taking advantage of a guidance signal. The objective functional typically consists of two parts: A fidelity term describes the consistency between input and output images, and a regularization term encourages the output image to have a similar structure to the guidance image [5]. The weighted least-squares (WLS) framework [4] is the most popular explicit regularization method that has been used in static guidance regularization [13]. The regularization term is modeled as a weighted l2 norm. Anisotropic diffusion (AD) [14] is an explicit regularization framework using dynamic guidance. In contrast to INM [2] and the RGF [6], AD updates both input and guidance images at every step;The regularization is performed iteratively with regularized input and updated guidance images. This explicit regularization enables formulating a task-specific model, with more flexibility than using implicit regularization. Furthermore, this type of regularization overcomes several limitations of implicit regularization, such as halos and gradient reversal, at the cost of global intensity shifting [4, 7]. Existing regularization methods typically apply to a limited range of applications and suffer from various artifacts: For example, the RGF is applicable to scale-space filtering only, and suffers from poor edge localization [17]. In contrast, B.Ham et al. approach provides a unified model for many applications, gracefully handles most of these artifacts, and outperforms the state of the art in all the cases considered in that paper [5]. Although the proposed model may look similar to WLS [4] and the RGF [17], their nonconvex objective function needs a different solver. Contrary to iteratively reweighted least-squares (IRLS) [3] regularizer but approximate the objective function by a surrogate (upper-bound) function.

3. Methodology

The project can be divided into two main parts. The methodology for each part will be discussed in following sections.

3.1. Sigma Estimation

IR imaging sensors are more complicated than visible light RGB sensors. One of the problems of IR sensors is higher amounts of noise. For most image processing applications, especially for image de-noising, there needs to be a way to measure image quality and enhancements between pre-algorithm and post-algorithm steps.

A widely used image quality metric is peak signal to noise ratio(PSNR). PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation[1]. For SNR measurements to work correctly, original image needs to be virtually noise-free.

Since original images are noisy in our case we will use two different methods to estimate noise levels from the original image. Then noise levels will be used as an image quality metric. Both methods were originally meant for additive white gaussian noise, this may or may not be the case for our dataset. Thus these methods need to be evaluated as well.

3.1.1 Online Variance Calculation on Consecutive Frames

3.1.2 Noise Level Estimation Using Weak Textured Patches of a Single Noisy Image

Noise Level Estimation Using Weak Textured Patches of a Single Noisy Image[11] uses low rank weak textured patches without high frequency components. Noise level is then estimated from selected patches using principal component analysis(PCA). Figure 1 shows the overall algorithm for this method.

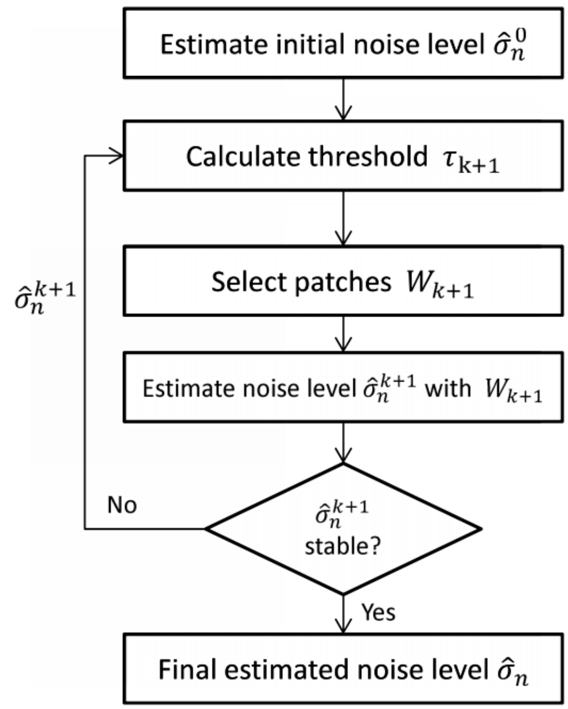

Figure 1. Algorithm for [11].

3.2. Filtering Framework

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4. Experiments

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