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SUPPRESSION OF DEFECTIVE DATA ARTIFACTS FOR DEBLURRING IMAGES CORRUPTED BY RANDOM VALUED NOISE*

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Abstract

For deblurring images corrupted by random valued noise, two-phase methods first select likely-to-be *reliables* (data that are not corrupted by random valued noise) and then deblur images only with selected data. Two-phase methods, however, often cause *defective data artifacts*, which are mixed results of *missing data artifacts* caused by the lack of data and *noisy data artifacts* caused mainly by falsely selected *outliers* (data that are corrupted by random valued noise). In this paper, to suppress these defective data artifacts, we propose a blurring model based reliable-selection technique to select reliables as many as possible to make all of to-be-recovered pixel values to contribute to selected data, while excluding outliers as accurately as possible. We also propose a normalization technique to compensate for non-uniform rates in recovering pixel values. We conducted simulation studies on Gaussian and diagonal deblurring to evaluate the performance of proposed techniques. Simulation results showed that proposed techniques improved the performance of two-phase methods, by suppressing defective data artifacts effectively.

Mathematics subject classification: 65F10.
Key words: Missing data artifacts, Normalization, Two-phase methods.

1. Introduction

The image deblurring is an ill-conditioned inverse problem, and the presence of random valued noise makes the problem more difficult. The random value noise corrupts some observed data with random values and leaves others unaffected. This type of noise is often generated by malfunctioning pixels in camera sensors, faulty memory locations in hardware, or erroneous transmission [5].

For the simplicity of the presentation, we use the term *outliers* to refer data that are corrupted by random valued noise, and *reliables* to refer data that are not corrupted by random valued noise.

Many methods have been proposed for deblurring images corrupted by random valued noise. Depending on what kind of data are used in deblurring, those methods can be categorized into following three groups: (a) 'simultaneous outlier-smoothing and deblurring' (data as observed) [2,3,22], (b) 'outlier-smoothing followed by deblurring' (smoothed data), and (c) 'reliable-selection followed by deblurring' (selected data as reliables) [7,8,13,21]. In particular, methods in the 'reliable-selection followed by deblurring' group are often called *two-phase*

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methods; they select likely-to-be reliables in the first phase, and deblur images only with selected data in the second phase.

It is well-known that methods in the 'simultaneous outlier-smoothing and deblurring' group often produce very poor results, even in the presence of very small amount of outliers [7]. Preprocessing outlier-smoothings might reduce such artifacts. Improvements made by outlier-smoothings are, however, often diminished out by errors made by outlier-smoothings themselves. For details, see [7].

Recent research works [7, 8, 13, 21] show superior performance of two-phase methods over 'simultaneous outlier-smoothing and deblurring' and 'outlier-smoothing followed by deblurring' methods. Two-phase methods can use various deblurring algorithms in the second phase. For instance, the Mumford-Shah regularization functional is used in [7] to achieve edge-preserving deblurring. In [8, 13], the L^1-norm of wavelet or framelet transforms is used to utilize sparse representations of images in wavelet or framelet transform domains. The method in [21] uses iterative two-phase approaches to improve the accuracy in reliable-selection.

Two-phase methods, however, often produce so-called *defective data artifacts*, which are mixed results of *missing data artifacts* caused by the lack of data and *noisy data artifacts* caused mainly by falsely selected outliers. Missing data artifacts can be suppressed, in some degree, by various *inpainting* algorithms [4, 6, 9]. In fact, two-phase methods in [7, 8, 13, 21] can also do inpainting. Inpainting algorithms, however, do not suppress missing data artifacts effectively in case when the missing data rate is high. We will explain such phenomenon in Section 3.1 of this paper. To suppress noisy data artifacts, many methods also have been developed. For details, see [7, 8, 13, 21] and references therein.

The objective of this paper is to improve the performance of two-phase methods, by effectively suppressing defective data artifacts. For this purpose, we propose *blurring model based reliable-selection* and *normalization* techniques.

Previous reliable-selection techniques (e.g., median-type approaches [10] and iterative projection comparison based reliable-selection [21]) tend to select reliables more frequently from smooth region than near-edge region. Such phenomenon often leads to the situation that no data are selected from a wide region. This often causes missing data artifacts. To avoid this kind of difficulty, the proposed blurring model based reliable-selection technique is designed to select reliables as many as possible, so that all of to-be-recovered pixel values contribute to selected data, while excluding outliers as accurately as possible.

The proposed normalization technique is designed to compensate for non-uniform rates in recovering pixel values; the selective use of data in two-phase methods causes some pixel values to be recovered more slowly than others in iterative deblurring. Such phenomenon often occurs on pixel values that give less contribution to selected data. To suppress this type of missing data artifacts, we suggest a normalization technique. This is a resulting algorithm derived from the use of a weighted inner product, which treats pixel values according to the degree of their contribution to selected data.

In this paper, we will explain the application of proposed techniques to a total variation (TV) [17] based two-phase method. Extensions to other two-phase methods in [7, 8, 13, 21] will be straightforward.

The outline of this paper is as follows. In Section 2, definitions, notations, and previous works are reviewed. In Section 3, proposed techniques are explained. In Section 4, simulation studies are conducted to test the performance of proposed techniques in Gaussian and diagonal deblurrings. Conclusions and discussions are presented in Section 5.