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A Novel Decomposition Framework For Gray Scale Image Denoising Algorithms

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Abstract— *Image processing applications like Image De-noising , Enhancement and Interpolation, Decomposition of the image into its components is a very effective technique., In this project, we consider an image decomposition model that provides a novel framework for image denoising. The model computes the components of the image to be processed in a moving frame that encodes its local geometry (directions of gradients and level lines). Then, the strategy we develop is to denoise the components of the image in the moving frame in order to preserve its local geometry, which would have been more affected if processing the image directly. Experiments on a whole image database tested with several denoising methods show that this framework can provide better results than de-noising the image directly, both in terms of Peak signal-to-noise ratio and Structural similarity index metrics.*

Keywords—decomposition; de-noising; components; local geometry; self-learning; moving frame;

I INTRODUCTION

Digital images play an important role both in daily life applications such as satellite television, magnetic resonance imaging, computer tomography as well as in areas of research and technology such as geographical information systems and astronomy. Image De-noising still remains a challenge for researchers because noise removal introduces artifacts and causes blurring of the images. The problem of removing the noise of an image while preserving its main features (edges, textures, colors, contrast, etc.) has been extensively investigated over the last two decades and several types of approaches have been developed [5].

To a great extent, these methods outperformed the de-noising models that existed at that time. Since then, a number of patch-based methods have been developed, comprising the majority of the current state-of-the-art de-noising methods. The current state-of-the-art de-noising methods are close to optimal when applied to natural images. Nonetheless, there is still room for improvement in several directions. For instance, while these methods manage to correctly remove most of the noise, they tend to not properly recover some of the image details. These methods also primarily deal with additive Gaussian noise, whereas for many images the noise model is unknown; in such cases, there is still ample room for improvement in below **fig-(exiting method)**.

Here introduce new approaches, which are a substantial extension of our earlier methods, show that given a de-noising method and obtain better, cleaner results by de-noising the components of an image, compared to what we would get by de-noising the image directly . That is, develop a strategy to improve any image de-noising technique by more carefully taking of the image to process.

DenoisedExisiting Method:

Existing Method

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II. IMAGE DECOMPOSITION METHODS

There are different techniques of image decomposition models and methodology observations. Some of which are following.

2.1. Methodology :

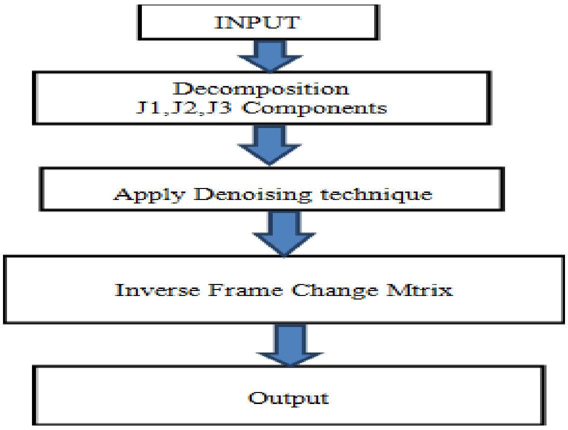


Fig.1: Methodology

2.2. Intrinsic image decomposition

Intrinsic image decomposition [2] is an ill-posed problem and cannot be solved without prior information on reflectance and illumination. This method is built based on well-established assumptions on reflectance and illumination and the Retinex algorithm [1]. The first assumption suggests that changes in reflectance are associated with changes in chromaticity, and the Retinex algorithm suggests that shading is smooth. Based on these assumptions, employed the prior on shading and reflectance as an image region with smooth intensity variations indicates constant reflectance. Thus, the reflectance of pixel *p* can be represented by the weighted summation of pixels in a set Ω that contains *p*, whose members have similar intensity compared to *p*.

Implementation steps of this approach are depicted in Figure 2. First, a smooth version of the input image was obtained via structure preserving image smoothing. Then, the smooth version of the image was used for intrinsic decomposition, and the shading and reflectance components were extracted. In the final stage, the texture information was added to either the shading or the reflectance component based on the material of each pixel.

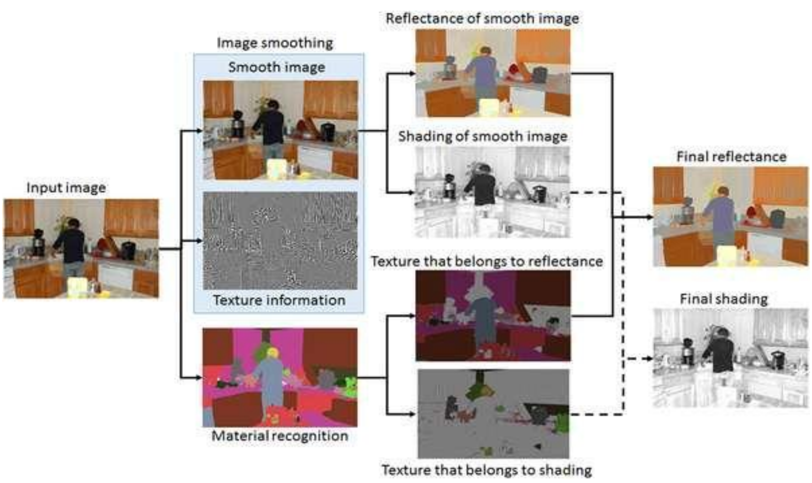


Figure 2. The proposed intrinsic image decomposition pipeline

2.2. Self-learning based image decomposition.

In this method [3], propose a self-learning based image decomposition framework. This method identifies image components based on semantical similarity and thus can be easily applied to the applications of image de-noising. Unlike prior learning-based image decomposition or De-noising works which require the collection of training image data (e.g., raw/noisy inputs vs. de-noised outputs, or low-resolution vs. high-resolution output images), this method advocates the self-learning of the input (noisy) image directly. After observing dictionary atoms with high spatial frequency (i.e., potential noisy patterns), advance the unsupervised clustering algorithm of affinity propagation without any prior knowledge of the number of clusters, which allows to automatically identify the dictionary atoms which correspond to undesirable noise patterns. As a result, removing such noise from the input image can be achieved by performing image reconstruction without using the associated dictionary atoms. From the above explanation, it can be seen that this method does *not* require any external training image data (e.g., noisy and ground truth image pairs), and *no* user interaction or prior knowledge is needed either. Figure 2 explains the decomposition model in detail.

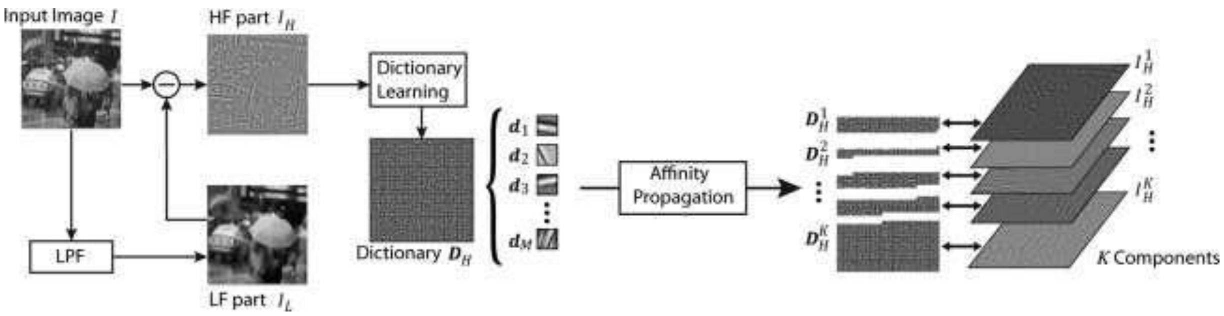
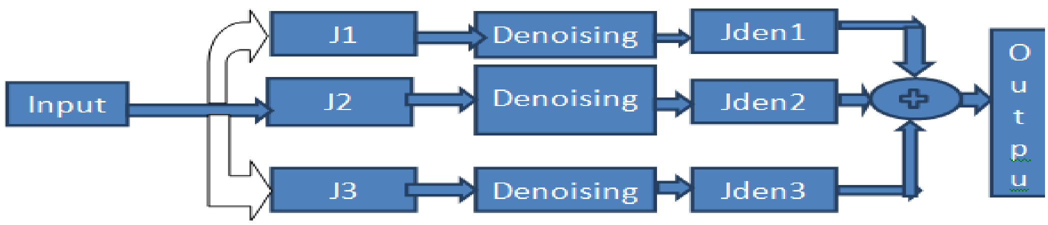


Figure 3. Self-learning based image decomposition



Proposed Method

2.3. Image decomposition using moving frame

In this method [4], developed a framework that enables any de-noising method to take more into account the local geometry of the image to be denoised by preserving the moving frame describing the graph of a scaled version of the image. An immediate benefit of this approach is that the de-noised

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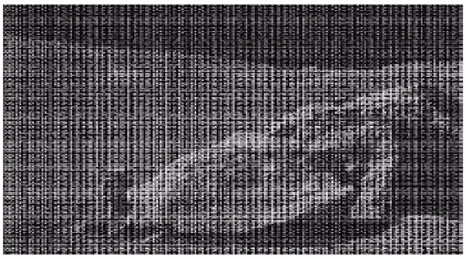
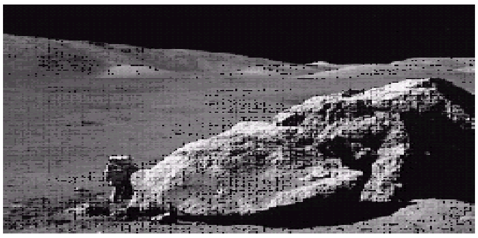
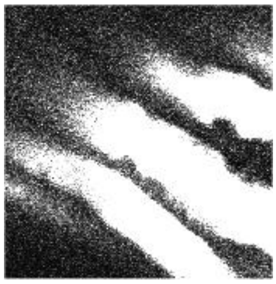


Before filtering



After filtering

image is obtained from its components in the moving frame using a straightforward invertible transform. This algorithm provides a new non-local method for image de-noising. The key idea that developed is to denoise the components of the image in a well-chosen moving frame instead of the image itself. This approach develop a strategy to improve any image de-noising technique by more carefully taking into account the local geometry (direction of gradients and level-lines) of the image to process.



Thermal imaging **Ultrasound Imaging Physical Interference**

III CONCLU SION

Different approaches for image decomposition are described. Through comparative study, the decomposition framework using moving frame approach is the most effective method. In this approach, it computes the components of the image to be processed in a moving frame that encodes its local geometry (directions of gradients and level lines). Then, the strategy denoise the components of the image in the moving frame in order to preserve its local geometry, which would have been more affected if processing the image directly.

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