A Review on Multi Scale Patch Based Image Restoration

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Abstract— Blind image restoration is used to in the Prior information of an image can often be used to restore the sharpness of edges. De-blurring is the process of removing blurring artefacts from images, such as blur caused by defocus aberration or motion blur. Motion blur is the apparent streaking of rapidly moving objects in a still image. A Gaussian blur is the result of blurring an image by a Gaussian function. The success of recent single-image methods partly stems from the use of various sparse priors, for either the latent images or motion blur kernels. De-blurring is the process of removing blurring artifacts from images, such as blur caused by defocus aberration or motion blur. Motion blur is the apparent streaking of rapidly moving objects in a still image. A Gaussian blur is the result of blurring an image by a Gaussian function. The success of recent single-image methods partly stems from the use of various sparse priors, for either the latent images or motion blur kernels. KSR also finds good kernel matrix approximation to speed up blurring and achieve good de-blur performances on digital datasets. As the unique identification of a vehicle, license plate is a key clue to uncover over-speed vehicles or the ones involved in hit-and-run accidents. We evaluate our approach on real-world images and compare with several popular state-of-the-art blind image de-blurring algorithms. Experimental results demonstrate the superiority of our proposed approach in terms of effectiveness and robustness.

Keywords: Image restoration, Deblurring

I. INTRODUCTION

Vision is the foremost trusted source of information compare to other human perceptions. And Image is the basic container of any pictorial information. The process of retrieving and analyzing the pictorial information by a digital computer is known as digital image processing. The improvement of pictorial information for human interpretation and processing of scene data for autonomous machine perception are the root application areas that had shown the interest in image processing field decades ago. Images in the real world are subject to various forms of degradation during image capture, acquisition, storage, transmission and reproduction. There are several attributes in images including blur, noise, contrast and saturation, which are directly related to above degradations. The task of an automated image quality inspection system is to make a reliable decision on image quality in near real time with minimum human involvement. In general, image quality measures can be classified into subjective or objective techniques. Subjective evaluation of image quality is costly and time consuming and the outcome of such an experiment would also depend on viewing conditions. Unlike subjective metrics, objective image quality metrics are faster and can produce immediate results while requiring minimum human involvement.

Before attempting to process the image for any useful information, it is critical to ascertain that the image being processed is of good quality. Among several quality attributes including blur, noise, contrast and saturation, image blur deteriorates high frequency contents in the image thereby making the image unworth for any useful information retrieval. Incorporating image blur detection in a camera will help discard bad image data at the source itself. Image blur detection for general purpose images is a challenging problem. Two primary sources for blur are relative motion between the camera and the object and poor focus. The purpose of a blur detection system is to eliminate missed detection s while achieving a low false alarm rate .

II. LITERATURE REVIEW

I. Ram, M Elad and I. Cohen [1] proposed an image-processing scheme based on reordering of its patches. For a given corrupted image, we extract all patches with overlaps, refer to these as coordinates in high-dimensional space, and order them such that they are chained in the "shortest possible path," essentially solving the traveling salesman problem. The obtained ordering applied to the corrupted image implies a permutation of the image pixels to what should be a regular signal. This enables us to obtain good recovery of the clean image by applying relatively simple one-dimensional smoothing operations (such as filtering or interpolation) to the reordered set of pixels. We explore the use of the proposed approach to image denoising and inpainting and show promising results in both cases.

P.Chatterjee and P.Milanfar [2] proposed a denoising method motivated by our previous analysis of the performance bounds for image denoising. Insights from that study are used here to derive a high-performance practical denoising algorithm. We propose a patch-based Wiener filter that exploits patch redundancy for image denoising. Our framework uses both geometrically and photometrically similar patches to estimate the different filter parameters. We describe how these parameters can be accurately estimated directly from the input noisy image. Our denoising approach, designed for near-optimal performance (in the mean-squared error sense), has a sound statistical foundation that is analyzed in detail. The performance of our approach is experimentally verified on a variety of images and noise levels. The results presented here demonstrate that our proposed method is on par or exceeding the current state of the art, both visually and quantitatively.

Ophir, M. Lustig and M. Elad [3] Proposed a multi-scale dictionary learning paradigm for sparse and redundant signal representations. The appeal of such a dictionary is obvious-in many cases data naturally comes at different scales. A multi-scale dictionary should be able to combine the advantages of generic multi-scale representations (such as Wavelets), with the power of learned dictionaries, in capturing the intrinsic characteristics of a family of signals. Using such a dictionary would allow representing the data in a more efficient, i.e., sparse, manner, allowing applications to take a more global look at the signal. In this paper, we aim to achieve this goal without incurring the costs of an explicit dictionary with large atoms. The K-SVD using Wavelets approach presented here applies dictionary learning in the analysis domain of a fixed multi-scale operator. This way, sub-dictionaries at different data scales, consisting of small atoms, are trained. These dictionaries can then be efficiently used in sparse coding for various image processing applications, potentially outperforming both single-scale trained dictionaries and multi-scale analytic ones. In this paper, we demonstrate this construction and discuss its potential through several experiments performed on fingerprint and coastal scenery images.

J.Mairal, M.Elad and G.Sapiro [4] Sparse representations of signals have drawn considerable interest in recent years. The assumption that natural signals, such as images, admit a sparse decomposition over a redundant dictionary leads to efficient algorithms for handling such sources of data. In particular, the design of well adapted dictionaries for images has been a major challenge. The K-SVD has been recently proposed for this task and shown to perform very well for various grayscale image processing tasks. In this paper, we address the problem of learning dictionaries for color images and extend the K-SVD-based grayscale image denoising algorithm that appears in . This work puts forward ways for handling nonhomogeneous noise and missing information, paving the way to state-of-the-art results in applications such as color image denoising and inpainting.

G. Plonka and J. Ma [5] Denoising is always a challenging problem in natural imaging and geophysical data processing. In this paper, we consider the denoising of texture images using a nonlinear reaction-diffusion equation and directional wavelet frames. In our model, a curvelet shrinkage is used for regularization of the diffusion process to preserve important features in the diffusion smoothing and a wave atom shrinkage is used as the reaction in order to preserve and enhance interesting oriented textures. We derive a digital reaction-diffusion filter that lives on graphs and show convergence of the corresponding iteration process. Experimental results and comparisons show very good performance of the proposed model for texture-preserving denoising.

M.Elad and M. Aharon [6] We address the image denoising problem, where zero-mean white and homogeneous Gaussian additive noise is to be removed from a given image. The approach taken is based on sparse and redundant representations over trained dictionaries. Using the K-SVD algorithm, we obtain a dictionary that describes the image content effectively. Two training options are considered: using the corrupted image itself, or training on a corpus of high-quality image database. Since the K-SVD is limited in handling small image patches, we extend its deployment to arbitrary image sizes by defining a global image prior that forces sparsity over patches in every location in the image. We show how such Bayesian treatment leads to a simple and effective denoising algorithm. This leads to a state-of-the-art denoising performance, equivalent and sometimes surpassing recently published leading alternative denoising methods.

III. PROPOSED WORK

In this process, we done the amount of prior information concerning the image and blur kernel as step one and then the algorithm used to perform restoration, then finally, the initial guesses made by the algorithm. Prior information of an image can often be used to restore the sharpness of edges. By contrast, there is no consensus concerning the use of prior information in the restoration of images from blur kernels, due to the complex nature of image blurring processes. Hence, we model a blur kernel as a linear combination of basic 2-D patterns. To illustrate this process, we constructed a dictionary comprising atoms of Gaussian functions derived from the 1-D Gaussian sequences. If objects in a scene are moving fast or the camera is moving over the period of exposure time, the objects or the whole scene will look blurry along the direction of relative motion between the object/scene and the camera. Due to the incorporation of this sparsity regularization, the de-blurred image suffers less from the undesirable ringing artifacts as well as noise amplifications. An effective sparse representation based blind image de-blurring method is presented. The proposed method exploits the sparsity prior of natural images to help alleviating the ill-posed inverse blind de-blurring problem.

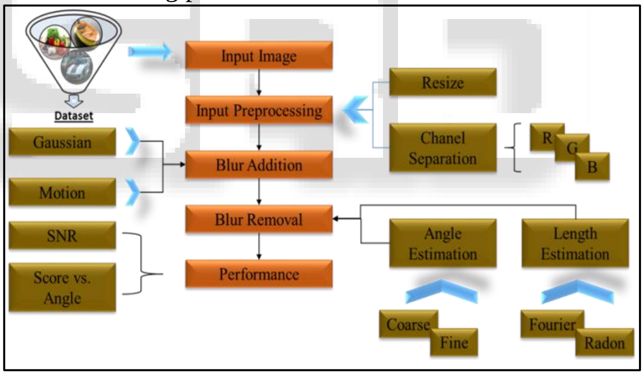

Fig. 1.1: Block Diagram

IV. CONCLUSION

The process of regularizing an unknown blur kernel largely determines the success of blind image restoration. In this process, we propose a novel approach to regularization in which a blur kernel is modeled as a representation of a tensor dictionary comprising basic 2-D patterns. The advantage of this approach is that it can be customized for a variety of applications simply by altering the design of the dictionary. To demonstrate, we constructed a dictionary with atoms formed by the Kronecker product of two 1-D scaled Gaussian functions. We also demonstrated that the solution of the approach can be derived by using the variable splitting method for image estimation and the proximal gradient method for blur kernel estimation.

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