Abstract

Images are affected by blur and noise during the acquisition process. The most prevalent visual artifact produced by the camera is space-variant blur due to finite aperture and shallow depth-of-field. Over the last few decades, several authors have addressed the blind image deblurring problem. However, finding an effective, reliable, and generally, applicable deblurring strategy continues to be a significant problem for the image processing research community. This thesis addresses the problem of deblurring an input space-variantly defocused image using non-local MRF-based priors such as Gauss-Markov (GMRF) and discontinuity adaptive random fields (DAMRF). An alternating minimization approach is adopted for searching for the optimal maximum a posteriori (MAP) estimate of proposed objective functions. Initially, we use the priors with a first-order local neighbourhood and then propose to exploit their non-local extensions. We also seek to search for non-local patches in external datasets and demonstrate superior performance for space-variant deblurring and denoising.

In the first chapter, we address the problem of restoration of a single space-variantly blurred image which is an ill-posed inverse problem. To obtain an initial coarse estimate of the space-variant blur kernels, we used a newly developed Just Noticeable Blur (JNB) approach. We obtain analytically the gradients of the proposed cost function with respect to the latent sharp image and the blur map. Experimental results demonstrate that the proposed cost function can be effectively optimized by utilizing the steepest descent technique to yield estimates of both the sharp latent image and the blur map. We first provide results using the GMRF prior and then compare them to the DAMRF regularizer. The DAMRF regularizer maintains characteristics such as edges and delicate texture. We provide both qualitative and quantitative comparisons of our algorithm with recent state-of-the-art methods.

In the second chapter, we investigate non-local extensions of GMRF and DAMRF priors for estimation of the restored image. The blur map corresponding to the space-variantly defocused input observation is also recovered simultaneously using GMRF and DAMRF priors with first-order local neighbourhoods. Since analytical expressions for both latent image and blur map are available, it is possible to use the steepest descent technique to optimize the proposed objective functions. Note that non-local patches are extracted from the input degraded observation only. In the previous chapter, we used priors with first-order neighbourhoods. Whereas here, we use non-local patches. We observe that many times the input observation consists of both focused and defocused regions. In order to extract only the defocused portion, we have used the local binary pattern feature. For minimization of the proposed cost function involving the DAMRF prior, we resort to the graduated non-convexity algorithm.

Further, in the third chapter, we propose to use an external dataset from which non-local patches are extracted. We harness non-local GMRF and non-local DAMRF priors for regularization, which leads to superior performance in the estimation of the latent sharp image and the blur kernels. The external

dataset created for this purpose consists of images captured by a DSLR camera and also by a microscope. We show the superiority of non-local priors using the proposed external dataset over non-local GMRF and DAMRF, wherein similar non-local patches are extracted using the same input observation through experiments on synthetic and real-world blurred images. We compare the results of our algorithm with state-of-the-art techniques and provide both qualitative and quantitative evaluations.

In the fourth work, we have addressed the problem of simultaneous denoising and deblurring images. For experiments using simulated data, original focused images are corrupted by space-invariant blur with a Gaussian point spread function and Gaussian noise. An external dataset consisting of pictures from BSD500, BSD68 and set12 datasets is used in our work. Experiments are carried out initially with GMRF and DAMRF priors with first-order local neighbourhoods. Then non-local extensions of both GMRF and DAMRF models are investigated wherein, firstly, non-local patches are extracted from the degraded observation itself. Finally, the proposed external dataset described above is utilized to extract similar non-local patches. Comparison results show the importance of using an external dataset during regularization with non-local GMRF and DAMRF priors, respectively. Statistical analyses and derivations are carried out on effective priors by utilizing non-local self-similar neighbourhood pixels information for denoising and deblurring. The objective function of our proposed work using alternating energy minimization is successfully optimized by the gradient descent method. We showed that the performance values of externel non-local (eNL) DAMRF prior are better than eNL GMRF prior. The edges, fine details, and structure information of the restored images generated by the eNL-DAMRF regularizer are better than several state-of-the-art works. We present the comparison results in terms of PSNR and SSIM scores.

Keywords: Guass-Markov Random field, discontinuity adaptive Markov random field, space-invariant deblurring, non-local means, graduated non-convexity algorithm