Decomposition based Color Image Restoration

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Abstract— Image decomposition is widely used technique to process the given grey or color image. Need of image restoration, in general, arises when the image is noisy or blurred. This paper addresses the issue of formulation of problem associated with the image restoration based on image decomposition. Along with this, the possible proposed approach is discussed. This paper is useful for the beginners in the image decomposition and image restoration.

***Index Terms*—Image Decomposition, Image Restoration, Noisy Image, Image Filtering.**

I. INTRODUCTION

Image restoration is required to restore the transmitted image or to recover the clear image from the distorted image. Image decomposition is the technique where the image is divided into different part or component to have the content of the image in different formats. While doing the decomposition, the properties of the image are preserved. This paper presents the formulation and the proposed approach for the image restoration based on the decomposition of the image. Firstly, the problem is formulated, and along with this the proposed approach is presented where one can explore different techniques to devise the proper mechanism for the image decomposition and restoration.

This paper is organized as follows. Section II discusses the related work; problem formulation and possible proposed approach is discussed in section III. Conclusion is given in section IV followed by the references.

II. RELATED WORK

Image decomposition is, basically, the representation of the given grey or color image in different parts or components so that later, the original image can be recovered. Existing approaches in [1]-[8] are studied and the methodologies used are- Learning based decomposition and then denoising [1], learning based artifact removal [2], intrinsic decomposition [3]-[6], texture and cartoon decomposition [7] and weighted least squares-based approach [8]. Summary of the studied approaches in [1]-[8] is summarized in Table 1.

Table 1: Image Decomposition Techniques Summary

Ref	Work Carried Out	Methodology	PEP	Dataset	Claim by author(s)	Our Findings
[1]	Self-learning-based image decomposition	Used sparse representation	PSNR	Rain images	Identified undesired noise patterns	Unsupervised clustering algorithm
[2]	Learning based artefacts removal	Bilateral filter, dictionary learning, sparse coding	Computational cost	Thorax & Pelvis Phantom	High image quality and low computational complexity	Enhanced the performance with less complexity
[3]	Image-space for estimating AO in image set	Per-pixel statistic & photometric approach used	RMSE, average error, LMSE	MIT intrinsic image dataset	Computation of reflectance and illumination without smoothness	No frame-by-frame ordering or coherence.
[4]	IID for classification of hyper spectral images	Feature extraction	Computational time	Indian Pines, the University of Pavia, and Salinas images	Higher classification accuracy with small training samples	No implementation of other hyper spectral applications
[5]	SSID for hyperspectral images	SLIC & FH	Computational time	Pavia dataset	Minimizes storage & computation requirements by using superpixels	Failed to take advantage of sparse constraints matrix
[6]	Image fusion based on IID	Reflectance prediction and reflectance + PAN image	Computational time	Quickbird and Worldview-2	Seamlessly fused images without spectral distortion	Computational cost is higher

[7]	Texture characterization-based image decomposition	Used BNN for suitable characterization	PSNR, SSIM	Berkeley segmentation Database	Handles blur + missing pixels images with different noise	Use of block wise nature of BNN is challenging
[8]	Edge preserving image decomposition	Weighted Least Square (WLS)	Application Specific Metric	Heart shaped cookies, Barbara, Girl, small office,	Feasible optimization framework	Method used in HDR tone mapping

Image restoration means to restore the original grey or color image from the distorted or noisy grey or color image. In general, different techniques are used to restore the original image, namely, denoising, deblurring, etc. Existing approaches in [9]-[21] are studied and the methodologies used are- Echo state network and optimization [9], wavelet [10], Gaussian mixture model [11], group sparsity [12], neural network [13], patch based [14], scale map [15], auto encoder [16], gradient sparsity [17], adaptive norm selection [18], p-norm [19], group sparse [20], and tensor recovery [21]. Summary of the studied approaches in [9]-[21] is summarized in Table 2.

Table 2: Image Restoration Literature Summary

Ref	Work Carried Out	Methodology	PEP	Dataset	Claim by author(s)	Our Findings
[9]	Differentiable error function based on the performance of losses	Denoising-Based approach	SSIM, SSIM, MSSIM	MIT-Adobe FiveK Dataset	Method can be acceptable by visual inspection	Choosing the right loss function is crucial
[10]	GSR using patches as base	Self adaptive dictionary learning	PSNR, FSIM	Barbara, Boats, House, C. Man, Peppers, Lena	Leverages both nonlocal self-similarity and intrinsic local sparsity	No solution for image deblurring in presence of impulse
[11]	Iterative denosing based image restoration	Off the shell denoiser	PSNR	Cameraman, House, Lena, Peppers, Barbara, Boat, Hill, Couple, BSD68	Utilizes fewer denoising NN for solving inverse problems	No high-quality results and computational efficiency
[12]	Non-local extension of total variation (TV) regularization	Sparsity model of gradient image	PSNR, SSIM	Lena, Peppers, Airplane, Barbara, Fishing boat, Sailboats	Estimation of each gradient and adaptive learning of statistical models	Handles non-stationery nature on images
[13]	Non-local variational technique based on SS for image restoration	SS-based nonlocal quadratic and total variation functions (SS-NLH1 and SS-NLTV) are used	PSNR, SSIM	USC-SIPI image database	Enhances the effectiveness of image restoration with texture and structural information	Addresses the limitations of intensity-based patch distance
[14]	Determining the optimal norms for both fidelity and regularization terms	Adopts Piecewise function and regularize norms	PSNR, Running Time	Cameraman, Barbera, Piret, Peppers, Leaf, Buildong, Aerial, Urban	Finds stable norm values regardless of noise type	Failed to seek an adaptive technique for determining an alternative in regularization
[15]	Gradient distribution based image restoration	Spatially variant hyper-Laplacian distribution is used	PSNR, SSIM	House, Peppers, Lena, Boat	Achieving better quality and texture preservation	No need of complex parameter tuning
[16]	Autoencoder based restoration for grayscale images	Auxiliary variable technique	PSNR, SSIM	Classic5 and LIVE1 dataset	Incorporates higher-dimensional structural information and enhances network stability.	For multi-filters either low rank regulation or sparse representation is required
[17]	Frameworks using different inputs like NIR image and noisy color image	Multispectral shadow detection is used	PSNR	NIR & noisy color images	Effectively handles structural divergence and achieves visually plausible image reconstruction.	Addresses the issues of multispectral image restoration
[18]	RNN based ESN for restoring image	Neurodynamic Optimization approach based on RNN	PSNR, MSE, NRMSE	Judd and Torallba dataset	Enhances the capabilities of ESNs for effectively recovering high-quality images from degraded or noisy versions.	Finding the optimal parameter is still a big challenge
[19]	Restoring images by representing them as	An edge-driven wavelet frame model	PSNR, Datagram	Slope, Angry Birds, Peppers,	Handles the estimation of image singularities and	Unsuitable for images with

	piecewise smooth functions	is used	Loss Rate	*Sonic, Train, Airplane, Oil Painting, and Pitt*	offers improved regularization	texture
[20]	Wavelet frame-based image restoration	Treating the images as a piecewise smooth function	SSIM	Car, Goldengate, Interior, Pitt, Samantha	Restores images by preserving singularities	Hindering the guarantee of both edges and sharpness.
[21]	Minimize the consequence of blur	Blind deconvolution method	Computation Cost	Debris Images	Minimizes expensive computations and improvement in debris analysis	Struggle to store fine textures

III. FORMULATION OF PROBLEM AND PROPOSED APPROACH

In general, it is found that the filtering banks can be used to decompose the images. In view of the development of the proposed filtering-based color image decomposition approach to address the issue of color image restoration, the baseline problem is formulated as follows:

Consider the color image *I* is firstly separated as the grey images (R-plane, G-plane and B-plane grey level images). That is,

R = {Intensity values from 0-255},

G = {Intensity values from 0-255},

B = {Intensity values from 0-255},

I = {R, G, B}

Later, each grey level plane is degraded with some noise η to get the degraded grey level plane images.

R_D*- Degraded R-plane with the insertion of noise* η.

G_D*- Degraded G-plane with the insertion of noise* η.

B_D*- Degraded B-plane with the insertion of noise* η.

Then these each degraded grey level planes (R_D, G_D, *and* B_D) are decomposed into three components in view of the color image restoration.

R_D*- Decomposed into* R_D-C_1, R_D-C_2, *and* R_D-C_3.

G_D*- Decomposed into* G_D-C_1, G_D-C_2, *and* G_D-C_3.

B_D*- Decomposed into* B_D-C_1, B_D-C_2, *and* B_D-C_3.

These three decomposed components (C_1, C_2, C_3) for each grey level plane can be obtained by using the combination of different filters or by using the typical filters
$F(\cdot)$ (*i.e.*, average filter, median filter, max filter, min filter, etc.). It is a matter of investigation to identify the particular filter which should be used only once or the filter banks or the combination of filters as shown in Figure 1.

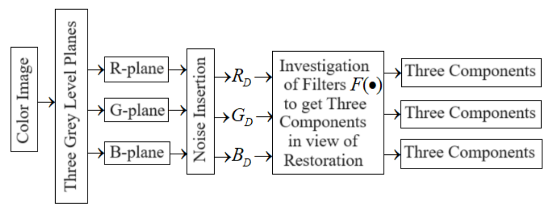

Figure 1: Filtering based Image Decomposition

Then these each degraded grey level planes (R_D, G_D, *and* B_D) are decomposed into three components in view of the color image restoration.

Being the proposed image restoration approach is based on the image decomposition and that is related to the filtering-based image decomposition, so, due consideration should be given to the noise percentage in the generated/decomposed three components of the degraded grey level plane images. And, later the development of the denoising/restoration mechanism to reconstruct the original color image by reconstructing grey level plane images. Reconstructed color image $I^{`}$ can be restored through the flow given in Figure 2.

By referring the presented problem formulation of image restoration based on image decomposition, one can investigate different filters from the image decomposition point of view. Various types of approaches can be developed based on filtering. It can be work out by using homogeneous or heterogeneous filters (*e.g.* simple average or median filters or the combination of average and median filters). If the original image is not distorted then the original image is degraded with the insertion of noise. And, then it is decomposed into three components. As these three components involves the noise, so it is necessary to evaluate the percentage of noise in these three components. Noise percentage evaluation may involve the use of variance and standard deviation. Finally, once done with the noise percentage evaluation, one can design the denoising mechanism to remove the noise in components to recover the noise free components which in turn produces the corresponding grey image or grey level plane of the color image. Reconstructed color planes can be combined to get the reconstructed color image.

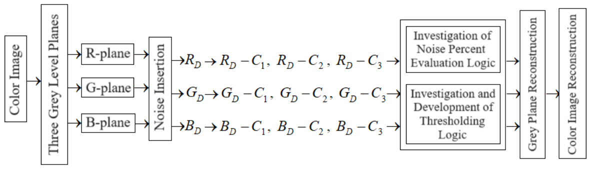

Figure 2: Decomposition based Image Restoration

IV. CONCLUSION

This paper discussed about the possible image decomposition and image restoration mechanisms or approaches. Different type of image decomposition approaches is possible and hence different type of image restoration approaches are possible. This paper is useful for the beginners in the domain of the image decomposition and image restoration.

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