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Image Noise Removal Techniques – A Personal Perspective and Assessment

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Abstract: Image noise removal has become an important research direction in the field of computer science because of the vast development and peaking demand of its applications.. Noise, the most common degrading factor, affects the visibility of the images and makes them unclear. Noise which is also called as an unwanted electrical or electromagnetic energy that degrades the quality of signals and data. Attenuation deteriorates the scene contrast and air light increases the whiteness in the scene. Therefore, the removal of attenuation and airlight helps to restore the color and contrast of the images, making them haze-free. Different works have been proposed till date inorder to filter out noise from images. This paper analyses the different image noise removal techniques. The different techniques, along with their merits and demerits are discussed.

Keywords: Denoising; Noise removal ; Image Processing ; Image restoration ;Power Spectral density;

I. INTRODUCTION

Due to motion or image reconstruction multispectral PAI can be effected by artifacts. Due to movement of an object such as breathing or heartbeat motion-based artifacts arise. Reconstruction-based artifacts can arise due to limited angle issues in back projection reconstruction algorithms. For instance, spatial under sampling can lead to streak artifacts during image reconstruction because of limited number of elements in the transducer array. In these contexts, denoising multispectral PAI and removing artifacts is a crucial procedure for further image processing and analysis such as image segmentation, spectral unmixing or co-registration.

Only reconstruction-based artifacts are targeted and in most cases artifacts are not removed completely but only reduced to a certain extent. Moreover, noise is not always guaranteed to be suppressed by there construction-based artifact removal methods. It is known that, if the imaging system is tomographic reconstruction algorithms and especially, improved variations of them, are able to suppress noise to some level through the superposition of projection signals in the image domain. However, in non-tomographic systems,the suppression does not give good results. Also, total variation regularization based on TVM or sparsity regularization based on L1 works well only when the true image is,infactsparse or has low variation.

This work, removes white noise and artifacts from in vivo multispectral PAI,where the level of noise and artifacts is not known a priori, and this refersimply as noise, though, keeping in mind the very different environment.This workproposes an analytical method based on Wiener filtering in the Fourier domain, where only Gaussian like filters having an anisotropic elliptical shapeare considered prior to minimizing MSE, and regularization is controlled bythe two parameters of thefilter. To minimize the mean squared error(MSE) between the observed and denoised images Wiener filter is constructed. However, a crucial assumption of Wienerfiltering is that the power spectral densities(PSDs) of noise and signal are known apriorior can be well estimated.While many PSD estimation methods exist in literature, they are usually applicable to time series.

The remainder of this paper is organized as follows: Related works in the literature of image haze removal are analyzed in Section II. Finally, a brief conclusion is given in Section III..

II. RELATED WORKS

This section gives an analysis on the various works that have been proposed in the area of image haze removal, stating both their merits and demerits.

In [1] authors proposes a framework for image denoising algorithms, an image decomposition model that provides a framework for image denoising. Themodel calculates the components of the image to be processed in a moving framethat encodes its local geometry. Thestrategy develop is to denoise the components of the image in the moving frame inorder to preserve its local geometry, which would have been more affected if proces sing the image directly. Experiments on a whole image database tested withmany denoising methods show that this framework can provide better results thandenoising the image directly, both in terms of Peak signal-to-noise ratio and Structural similarity index metrics.The problem of removing the noise of an image whilepreserving its main features (edges, textures, colors, contrast, etc.) has been extensively investigated over the last two decades and several types of approaches havebeen developed. The total variation-based denoising method had a great impact inthe imaging community and has inspired a large amount of variational formulationsfor image denoising. Years after the model of Rudin, a novel approach for image denoising based on the comparison of pixel neighborhoods (patches) was proposed simultaneously with the UINTA algorithm with the Non-Local Means (NLM) algorithm. To a great extent, these patch based methods outperformed the denoisingmodels that existed at that time. Since then, a number of patch-based methodshave been developed, comprising the majority of the current state-of-the art denoising methods. It has been shown that the current state-of-the-art denoising methodsare close to optimal when applied to natural images. None the less, there is stillroom 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 ofthe image details. These methods also primarily deal with additive Gaussian noise,whereas for many images the noise model is unknown. Our proposal in this paper is to develop a strategyto improve any image denoising technique by more carefully taking into account thelocal geometry (direction of gradients and level-lines) of the image to process In [2] authors proposes adaptive image denoising by mixture adaptation, an adaptive learning procedure tolearn patch-based image priors for image denoising. The algorithm, calledthe expectation-maximization (EM) adaptation, will take a generic prior learned froma generic outer database and adapts it to the noisy image to generate a specificprior. Different from existing methods that combine internal and external statisticsin ad hoc ways, the proposed algorithm is rigorously derived from a Bayesian hyperprior perspective. There are two contributions of this paper. First, it provide fullderivation of the EM adaptation algorithm and manifest methods to modify thecomputational complexity. Next, in the absence of the latent clean image, it showhow EM adaptation can be modied based on pre-filtering. The experimental resultsshows that the proposed adaptation algorithm yields consistently better denoisingresults than the one without adjustment and is superior to several state-of-the-artalgorithms. Method proposes an EM adaptation method to learn effective imagepriors. The proposed algorithm is rigorously derived from the Bayesian hyper-priorperspective and is further simplied to reduce the computational complexity. In theabsence of the latent clean image, method proposes modications of the algorithmand analyzed how some internal parameters can be automatically estimated. Theadapted prior from the EM adaptation better captures the prior distribution of theimage of interest and is consistently better than the un-adapted generic one. In thecontext of image denoising, experimental results demonstrate its superiority oversome existing denoising algorithms, such as EPLL and BM3D. Future work includesits extended work on video denoising and other restoration tasks, similar to deblurringand inpainting.

In [3] authors proposes blind deblurring and denoisingof images interrupted by unidirectional object motion blur and sensor noise a noveltechnique to recover a dense estimate of spatially varying blur kernel as well as adenoised as well as deblurred image from a single noisy and object motion blurred image.Proposed method takes the merit of the sparse representation of double discrete wavelet transform a generative model of image blur that simplifies the waveletanalysis of a disturbed image and the Bayesian perspective of modeling the prior distribution of the latent sharp wavelet coefficient and the likelihood function that makesthe noise handling explicit. Demonstrate the effectiveness of the proposed methodon moderate noise and severely disturbed images using simulated and real cameradata.

In [4] proposes blind image denoising via dependent dirichlet process tree the model to resolvethe problem of unknown noisy models. Earlier existing image denoising approachesexpected the noise to be homogeneous white Gaussian distributed noise with known intensity. However, in real noisy images, the noise models are usually unknown beforehand and can be much more complex. The paper addresses this problem andsuggest a novel blind image denoising algorithm to recover the clean image fromnoisy one with the unknown noise model. To model the empirical noise of an image, our method introduces the mixture of Gaussian distribution, which is changeableto approximate different continuous distributions. The difficulty of blindimage denoising can be named as a learning problem. The method is to build a two-layer structural model for noisy images and consider the clean onesas latent variable. To control the complexity of the noisy patch mock-up this workproposes a novel Bayesian non parametric prior called Dependent Dirichlet ProcessTree to build the model. Then, this study derives a variational inference algorithmto estimate model parameters and recover clean patches. This method applies onsynthesis and real noisy images with different noise models. Comparing with previous approaches, this method achieves better presentation. The experimental outputsindicate the effectiveness of the proposed algorithm to cope with practical image denoising tasks. The Dirichlet Process species a distribution over the space of probability measures on a measurable space , each draw of a Dirichlet Process is also a distribution. It is parameterized by the concentration parameter α and base measurementH. Method proposes a learning-based approach to automatically recover the cleanimage from the observed noisy one. The noise model is unknown and modeled with aMoG. The clean patches are assumed to lie in several local subspaces. Method builta two-layer structural mixture model for noisy patches and treat the clean onesas latent variables. To build the model, method proposes the dependent Dirichlet process tree as prior, which is a novel non parametric prior that introduces amechanism of parameters sharing among mixtures. A variational inference algorithm was proposed accordingly to estimate both the model and the clean patchesas latent variables. Extensive experiments were conducted to test the performanceof this approach on images contaminated by different noise. Method achieved the best performance among competitive algorithms, preserving detailed features andeliminating noise with different models. These features make our method a bettercandidate in handling real-world image denoising tasks.

In [5] authors proposes dynamic denoising oftracking sequences describe an approach to the problem of simultaneously enhancing image sequences and tracking the objects of interest represented by the latter.The enhancement part of the algorithm is based on Bayesian wavelet denoising,which has been selected due to its exceptional ability to incorporate diverse a prioriinformation into the process of image recovery. In particular, method demonstratesthat, in dynamic settings, useful statistical priors can come both from some reasonable assumptions on the properties of the image to be enhanced as well as fromthe images that have already been observed before this scene. Using suchpriors forms the main donation of the present paper is the proposal ofthe dynamic denoising as a device for simultaneously enhancing and tracking imagesequences. Within the proposed framework,the earlier observations of a dynamicscene are employed to enhance its present observation. The procedure that allowsthe fusion of the information with in successive image frames is Bayesian estimation, while transmitting the useful information between the images is governed bya Kalmanfilter that is applicable for both prediction and estimation of the dynamics oftracked objects. Therefore,in this methodology,the method of target tracking andimage enhancement collaborate in an interlacing manner,other than being appliedseparately. The dynamic denoising is demonstrated on several examples of SARimagery. The results demonstrated in this paper indicate a number of advantagesof the proposed dynamic denoising over static proceed towards, in which the trackingimages are enhanced independently of each other. Whenever reasonable assumptions on the statistical properties of an image of interest will be made, the Bayesianapproximation framework often allows one to derive a considerably more informativeevaluate of the image as compared to the case when the estimation is performedbased on observed data alone. This is why Bayesian estimation has long become apreferred method of reconstructing signals and images, basically in the situationswhen a priori assumptions are important to either recover lost information or fusemultiple informational sources . Unfortunately, dening the priors is well-known tobe a very delicate step that, when performed incorrectly, could produce rather misleading results. The central idea of the present study has been to show conceptuallyand experimentally that, in dynamic framework, some useful priors can be extractedfrom previous observations of the dynamic scene that needs to be enhanced. Asa result, an image enhancement procedurereferred to as DDNwas introduced as amethod for simultaneously magnifying sequences of images and tracking the objects of interest represented by the latter In [6] authors proposes image denoising by exploring external and internal correlations , image denoisingsuffers from limited data collection within a noisy image. Method proposes a novel image denoising scheme, which explores both internal and external correlations withthe help of web images. For each noisy patch, method build internal and externaldata cubes by finding similar reinforcement from the noisy and web images, respectively.Method then proposes reducing noise by a two-stage strategy using different filtering approaches. In the initial stage, since the noisy patch may lead to inaccuratepatch selection, method proposes a graph based optimization method to improvepatch matching accuracy in outer denoising. The internal denoising is frequencytruncation on internal cubes. By combining the internal and external denoisingpatches,obtain a preliminary denoising result. In the second stage, method proposesreducing noise by filtering of external and internal cubes, respectively, on change domain. In this stage, the preliminary denoising result not only enhances the patchmatching accuracy but also provides reliable estimates offiltering parameters. The final denoising image is obtained by fusing the external and internal filtering results.

Experimental output show that this method constantly outperforms state-of-the-artdenoising schemes in both subjective and objective quality computation, e.g., itachieves greater than 2 dB gain compared with BM3D at a wide range of noise levels.

In [7] authors proposes image denoising via bandwise adaptive modeling andestablishment exploiting nonlocal similarity, method proposes a new image denoising algorithm based on adaptive signal modeling and regularization. It upgradesthe condition of images by regularizing each image patch using bandwise distribution modeling in change domain. Instead of using a global model for all thepatches in an image, it employs content-dependent adaptive models to address theperiod to period of image signals and also the diversityamong different transformbands. The distribution model is adaptively estimated for each patch individually.It varies from one patch location to another and also varies for dfferent bands . Inparticular, consider the estimated distribution to have non-zero expectation. Toestimate the assumption and variance parameters for every band of a particularpatch, exploit the nonlocal correlation in image to collect a set of highly similarpatches as the data samples to form the distribution. Irrelevant patches are excluded so that such adaptively-learned model is more accurate than a global one.The image is ultimately restored via bandwise soft-thresholding, based on Laplacian approximation of the distribution of similar-patch group transform coefcients. Experimental outputs demonstrate that the proposed scheme outperformsseveral state-of-the-art denoising techniques in both the objective and the perceptualqualities.

In [8] Michael Elad and Michal Aharon proposes image denoising via sparseand redundant representations over learned dictionaries,this method addresses theimage denoising problem, where zero-mean white and homogeneous Gaussian additive noise is to be removed from a given image. The approach taken is based onsparse and redundant representations over trained dictionaries. Using the K-SVDalgorithm, obtain a dictionary that describes the image content effectively. Twotraining options are considered: using the corrupted image itself, or training ona corpus of high-quality image database. Since the K-SVD is limited in handlingsmall image patches, extend its deployment to arbitrary image sizes by dening aglobal image prior that forces sparsity over patches in every location in the image. Method shows how such Bayesian treatment leads to a simpleeffective denoising algorithm. This leads to a state-of-the-art denoising performance, equivalent and sometimes surpassing recently published leading alternative denoising methods

In [9] authors proposes image denoising with edge-preserving and segmentation based on mask NHA , a zero-mean white Gaussian noise removal methodusing a high-intention frequency analysis. It is touph to separate an original imagecomponent from a noise component when using discrete Fourier transform or discrete cosine transform for analysis because side lobes occur in the outcome. The

2Dnon-harmonic analysis (2D NHA) is a high-intention frequency analysis techniquethat raises noise removal accuracy because of its side lobe reduction feature.However, spectra generated by NHA are misrepresented, because of which the signal of the image is non-stationary. Method analyze each region with a homogeneous texture in the noisy image. Non-uniform regions that occur due to segmentation areanalyzed by an extended 2D NHA method called Mask NHA. Conducted an experiment using a simulation image, and found that Mask NHA denoising achieves ahigher peak signal to-noise ratio (PSNR) benefit than the state-of-the-art methods ifa suitable segmentation result can be obtained from the specified image, even thoughparameter optimization was incomplete. This experimental result manifest clearly the upperlimit on the value of PSNR in our Mask NHA denoising method. The executionof Mask NHA denoising is expected to move nearer the limit of PSNR by improvingthe segmentation method.

In [10] ShibinParameswaran, Enming Luo and Truong Q. Nguyen proposespatch matching for image denoising using neighborhood-located collaborative filteringconsider patch matching as a recommendation structure problem and introduce a newpatch matching approach which uses nearest neighbor-based collaborative filtering(NNCF).This approach involves recommending similar patches to a query patch with thehelp of other similar patches in a noisy image or an outer database. Using useroriented and item-oriented formulations of NN-CF, present two variations of CFbased patch matching criterion. To demonstrate the superior matches found from our method,apply the new patch matching scheme to patch-based image denoising and evaluate its effect on the denoising performance. Test the methods on twodatasets with varying framework and image complexities and underdifferent levelsof noise. The proposed method not only improves robustness to patch matchingbut also supplies a new formulation to seamlessly combine internal and externaldenoising.

In [11] Claude Knaus and Matthias Zwicker proposes progressive image denoising, presented image denoising as a physical process, which can be summarized inthree points.First, perform a gradient descent by progressively estimating noise differentials and subtracting them iteratively from the noisy image. Next, the noisedifferentials are estimated using robust kernels in two spatial province, one spatialrange domain and one frequency range domain. Third, the kernel scale parametersare modified according to an annealing schedule. This approach using robust estimators unifies spatial and wavelet domain methods. Method considered denoisingas robust noise estimation in multiple dimensions and domains. In each dimensionand domain, the noise estimation is protected from bias by using redescendingestimators. This perspective allowed reinterpret wavelet shrinkage as robust noiseestimation. Method also connected image denoising to statistical mechanics. Alike to deterministic annealing, change the shape of the robust noise estimator overtime. The scale parameter of the range kernel corresponds to the falling temperature in deterministic and simulated annealing. This annealing process allows to find near-optimal solutions. In contrast to current state-of-the-art denoising methods, algorithm is short. Despite its simplicity, the algorithm conveys high-qualityresults, out performing other methods in denoisingsynthetic images. Thinking aboutthat many methods already work well enough for natural images, the new challengeis in denoising synthetic images. State-of-the-art denoising methods are currentlytoo slow for integration into consumer products. Since method focused on qualityand simplicity rather than performance, there remains a terrain to explore acceleration of denoising process. Finally, believe that our contribution is not limited toimage denoising. An avenue of investigation would be to find out how our denoisingapproach impacts related problems like artifact removal, superresolution then the holefilling. Denoising formulation is agnostic of dimensionality of the wave. Consequentlyexpect that contribution to be of interest to the signal processing community atlarge and to many domain specific applications.

In [12] authors proposes tensordecomposition and PCA jointed algorithm for hyperspectral image denoising ,denoising is a critical preprocessing step for hyperspectral image (HSI) classificationand detection. Traditional methods usually convert high-dimensional HSI data to2-D data and process them unrelated. Consequently, the inherent structured high dimensional information in the original observations may be no longer useful. To overcomethis disadvantage, this letter tackles an HSI denoising by jointly exploiting Tuckerdecomposition and principal component analysis (PCA). A truncated Tucker decomposition method based on noise power ratio (NPR) analysis and jointed withPCA is presented. This method call this jointed method as NPR-Tucker+PCA..Experimental results show that the proposed method outperforms existing methodsin the sense of peak signalto-noise ratio performance. This letter proposes an HIS denoising method by jointly exploiting tucker tensor decomposition and PCA basedon NPR analysis. Moreover, PCA is jointly applied to preservefine image featuresand remove residual noise. Although its computational complexity is slightly higherthan Shrinkage+PCA, computational complexity is relatively not that importantsince real-time processing is usually not required in HSI postprocessing

III. CONCLUSION

In this work, the problem of artifact removal and denoising of multispectral photoacoustic images was considered. This study focused towards in-vivo images, where the level of noise is not known a priori. The regularized Wiener filter ing in Fourier domain was applied, where only a family of filters having an anisotropic elliptical shape was considered and regularization was achieved by the two radii of an ellipse. Although in the presented experiments nearly round filter shapes were favored, the method remains flexible and can be applied to the cases, where edges are distributed mostly along one of the two axis in the frequency domain.

Using standard Wienerfiltering in Fourier domai n does not help us to remove high frequency components which we assume to be noise. To account for this, construct new filter. To investigate the smearing and white noise removal capabilities of the proposed method, we used purely simulated multispectral PAI data which mimics the optical properties of biological tissue. For this, we used constructed absorption and scattering dictionaries based on in-vivo data of the main absorbers: Hb, HbO2, melanin, water and fat, as well as the main scattering media: brain, skin, breast, bone and fatty tissues. These absorption and scattering spectral signatures were then weighted by simulated weights which followed non negativity and sum-to-one constraints to obtain the original object.

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