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# SURVEY ON VARIOUS APPROACHES FOR ENHANCEMENT OF DIGITIZED IMAGES AND DIGITAL VIDEOS

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**Abstract:**
Digital videos may be degraded by several spatial and temporal corrupting factors which include but are not limited to noise, blurring, ringing, blocking, flickering, and other acquisition, compression or transmission artifacts. In view of the joint presence of random and fixed-pattern noise (FPN), the FPN typically arises in raw images acquired by focal plane arrays (FPA), such as CMOS sensors or thermal micro bolometers, where spatial and temporal non uniformities in the response of each photo detector generate a pattern superimposed on the image approximately constant in time. The spatial correlation characterizing the noise corrupting the data acquired by such sensors invalidates the classic additive white Gaussian noise (AWGN) assumptions of independent and identically distributed and hence white– noise. The FPN removal task is prominent in the context of long wave infrared (LWIR) thermography and hyper spectral imaging. Existing denoising methods can be classified into reference-based (also known as calibration-based) or scene based approaches. Reference-based approaches first calibrate the FPA using (at least) two homogeneous infrared targets, having different and known temperatures, and then linearly estimate the non-uniformities of the data. However, since the FPN slowly drifts in time, the normal operations of the camera need to be periodically interrupted to update the estimate which has become obsolete. Differently, scene-based approaches are able compensate the noise directly from the acquired data, by modeling the statistical nature of the FPN. This survey paper elaborates various approaches for noise removal and advancements in the image.

## Introduction

For the past decades, noise-removal methods based on partial differential equations have become a powerful and well-founded tool in image analysis. Among numerous partial differential equations-based approaches, the filters formulated by nonlinear partial differential equations have tremendous and impressive results. For additive noise removal, lot of work have been demonstrated that the nonlinear diffusion methods can remove additive noise and simultaneously preserve or even enhance semantically important information such as edges, lines, or textures. However, in the case of multiplicative noise removal, there are few partial differential equations -based models which steer the whole noise removal process in the view of nonlinear diffusion equations. In case of Raw High Frame Rate Videos, high frame rate cameras capture sharp videos of highly dynamic scenes by trading off signal-noise-ratio and image resolution, so combinational super-resolving and denoising is crucial for enhancing high speed videos and extending their applications.

Recent advancements in image acquisition and visual computing made technology cheaper and easily available, consequently putting more power into the hands of an average user. High quality cameras, standalone or integrated into mobile devices, as well as advanced image editing tools are more commonly used than ever.

## 1. Literature Review

Zhenyu Zhou, Zhichang Guo, Gang Dong, Jiebao Sun, Dazhi Zhang, Boying Wu [1], proposed, a doubly degenerate nonlinear diffusion equation model for multiplicative noise removal. A nonlinear diffusion filter denoising framework which takes into account not only the information of the gradient of the image, but also the information of gray levels of the image. a doubly degenerate diffusion model for multiplicative noise removal, which is analyzed with respect to some of its properties and behavior in denoising process.

Chuan Chen, Michael K. Ng, and Xi-Le Zhao [2] addressed the total variation (TV)-based nonlinear image restoration problems. In nonlinear image restoration problems, an original image is corrupted by a spatially invariant blur, the build-in nonlinearity in imaging system, and the additive Gaussian white noise. By making use of the structure of the objective function, an efficient alternating direction method of multipliers developed the proposed model. The convergence of the numerical scheme is also considered. Numerical examples, including nonlinear image restoration and high-dynamic range imaging are reported to demonstrate the effectiveness of the said model and the efficiency of the numerical scheme.

Lucio Azzari and Alessandro Foi [3] demonstrated the feasibility of the approach through an extensive theoretical analysis based on mixture of Gaussian distributions. A prototype algorithm is also developed in order to validate the approach on simulated data as well as on real camera raw images.

Jinli Suo, Yue Deng, Liheng Bian and Qionghai Dai [4], proposed, scheme for noise separation and super resolution under a unified optimization framework, which models both spatiotemporal priors of high quality videos and signal-dependent noise. Mathematically, alignment of the frames along temporal axis has been done and pursued the solution under the following three criterion: 1) the sharp noise free image stack is low rank with some missing pixels denoting occlusions; 2) the noise follows a given nonlinear noise model; and 3) the recovered sharp image can be reconstructed well with sparse coefficients and an over complete dictionary learned from high quality natural images.

Matteo Maggioni, Enrique Sánchez-Monge, and Alessandro Foi [5], proposed a framework for the denoising of videos jointly corrupted by spatially correlated (i.e., nonwhite) random noise and spatially correlated fixed-pattern noise. The approach is based on motion-compensated 3D spatiotemporal volumes, i.e., a sequence of 2D square patches extracted along the motion trajectories of the noisy video. First, the spatial and temporal correlations within each volume are leveraged to sparsify the data in 3D spatiotemporal transform domain, and then the coefficients of the 3D volume spectrum are shrunk using an adaptive 3D threshold array. Such array depends on the particular motion trajectory of the volume, the individual power spectral densities of the random and fixed-pattern noise, and also the noise variances which are adaptively estimated in transform domain.

Stanley H. Chan, Member, IEEE, Todd Zickler [6], proposed a randomized version of the nonlocal means (NLM) algorithm for large-scale image filtering. The new algorithm, called Monte Carlo nonlocal means (MCNLM), speeds up the classical NLM by computing a small subset of image patch distances, which are randomly selected according to a designed sampling pattern. Two contributions have been done. First, analyzed the performance of the MCNLM algorithm and shown that, for large images or large external image databases, the random outcomes of MCNLM are tightly concentrated around the deterministic full NLM result. In particular, the error probability bounds showed that, at any given sampling ratio, the probability for MCNLM to have a large deviation from the original NLM solution decays exponentially as the size of the image or database grows. Secondly, explicit formulas have been derived for optimal sampling patterns that minimize the error probability bound by exploiting partial knowledge of the pairwise similarity weights. Numerical experiments show that MCNLM is competitive with other state of-the-art fast NLM algorithms for single-image denoising.

Wensen Feng, Hong Lei, and Yang Gao [7], proposed two novel models for removing multiplicative noise based on total generalized variation (TGV) penalty. The TGV regularization has been mathematically proven to be able to eliminate the stair casing artifacts by being aware of higher order smoothness. Furthermore, an efficient algorithm is developed for solving the TGV-based optimization problems. Numerical experiments demonstrate that our proposed methods achieve state-of-the art results, both visually and quantitatively. In particular, when the image has some higher order smoothness, the methods outperform the TV-based algorithms.

Zhengguo Li, Senior Member, IEEE, Jinghong Zheng, [8], a weighted guided image filter (WGIF) is introduced by incorporating an edge-aware weighting into an existing guided image filter (GIF) to address the problem. The WGIF inherits advantages of both global and local smoothing filters in the sense that: 1) the complexity of the WGIF is O(N) for an image with N pixels, which is same as the GIF and 2) the WGIF can avoid halo artifacts like the existing global smoothing filters. The WGIF is applied for single image detail enhancement, single image haze removal, and fusion of differently exposed images. Experimental results shows that the resultant algorithms produce images with better visual quality and at the same time halo artifacts can be reduced/avoided from appearing in the final images with negligible increment on running times.

Tunc¸ Ozan Aydın, et.al [9], presented a perceptually calibrated system for automatic aesthetic evaluation of photographic images. The work builds upon the concepts of no-reference image quality assessment, with the main difference being focused on rating image aesthetic attributes rather than detecting image distortions. In contrast to the recent attempts on the highly subjective aesthetic judgment problems such as binary aesthetic classification and the prediction of an image's overall aesthetics rating, the method aims on providing a reliable objective basis of comparison between aesthetic properties of different photographs.

Nunnagoppula, G. Infosys Labs., Infosys Ltd., India, et. al. [10] proposed, automatic blur detection method in mobile captured documents images. They proposed a simple method that addresses some challenges faced in these document images. Extensive testing is performed on large dataset containing more than 4000 mobile captured images and optimum parameter values for performing quality check against motion blur and defocus are identified.

Simon Lucey, et. al. [11], demonstrated a novel extension to LK algorithm and AAM fitting algorithm which allows for them to be equivalently cast in the Fourier domain. This formulation allows to interpret the joint alignment across multiple filter responses as a form of the weighted LK algorithm. Proposed research presented a method to do image and object alignment using a bank of filters that encode local relative intensity (e.g., Gabor filters).

Charles-Alban Deledalle, Loïc Denis, Florence Tupin, Andreas Reigber, and Marc Jäger, [12], proposed fully automatic method and handles single and multi-look images, with or without interferometry or Polari metric channels. Efficient speckle reduction with very good resolution preservation is demonstrated both on numerical experiments using simulated data, airborne, and space borne radar images.

Gabriel Ramos-Llordén, et. al. [13], proposed an anisotropic diffusion filter with a probabilistic-driven memory mechanism to overcome the over-filtering problem by following a tissue selective philosophy. In particular, formulation has been carried out using the memory mechanism as a delay differential equation for the diffusion tensor whose behavior depends on the statistics of the tissues, by accelerating the diffusion process in meaningless regions and including the memory effect in regions where relevant details should be preserved.

Laurent Caraffa, Jean-Philippe Tarel∗, Pierre Charbonnier, [14], proposed a methodology to handle non-Gaussian noise on the guide image, even if both are strongly correlated. This allows the Guided bilateral filter to handle situations with more noise than the Joint/Cross bilateral filter can work with and leads to high Peak Signal to Noise Ratio PSNR.

## 2. Approaches for Image Enhancement

Paper discusses the various methods for obtaining high quality image enhancement suggested by different researchers.

### a. Automated Aesthetic Analysis

From the user's point of view, these new technologies create the expectation of more appealing images. But obtaining appealing results requires not only advanced tools, but also the knowledge and execution of basic aesthetic principles [9] during acquisition and editing. The problem is that the average user does not always have the necessary training and experience, nor the interest in acquiring them. Thus, modeling aesthetic principles and building systems that give automatic aesthetic feedback is a research area with high practical relevance. Image Intelligence framework that utilizes multiple systems (such as light source recognition, face detection, etc.) to improve image aesthetics, While automatic aesthetic judgment is useful for many practical purposes, such judgments the in form of a yes/no answer, or a percentage score do not explain why the evaluated image is aesthetically pleasing or not. This is because when designing such systems, understandably the image features are selected based on their classification performance of overall aesthetics, but not necessarily on how well they correlate with the aesthetic attribute they claim to evaluate. As an example, it is often not discussed if a "clarity" feature actually corresponds to what people consider as the photographic clarity rule, or is some abstract heuristic that happened to result in accurate classification. While this approach is perfectly fine for predicting a single-dimensional outcome, a multi-dimensional aesthetic analysis based on ratings of meaningful aesthetic attributes requires a different approach and poses additional challenges.

The first challenge is finding a set of image attributes that are simple enough to be expressed as computer programs, but at the same time are closely related to some fundamental photographic attributes. Once these attributes are defined, another challenge is designing and executing a subjective study through which one can reliably determine ground truth attribute ratings on a set of real world images. Once the subjective data is obtained, the final challenge is the design, implementation and calibration of metrics that predict a rating for each aesthetic attribute.

**Aesthetic Attributes**

One of the main challenges of automated image aesthetics is identifying a set of aesthetic attributes that can be expressed algorithmically, and are closely related to photographic principles they claim to model. Since it is practically impossible that a computational system accounts for every photographic rule, one needs to determine some guidelines for choosing some aesthetic attributes over others. The following criteria determine the set of aesthetic attributes:

Generality: While sharpness is relevant in every photograph, a more specific attribute such as facial expression is only useful for photographs with people.

Relation to photographic rules: From a modeling point of view it may be desirable that the aesthetic attributes are orthogonal to each other. However this would also require to invent new, artificial attributes that are not necessarily meaningful to humans, since in reality the photographic rules are not always orthogonal.

Clear definition: In photography literature photographic rules and practices are often communicated through examples rather than mathematical formulas or concrete statements.

Pictures with no scene elements in focus are often conceived as photographic errors. In fact, sharpening the in-focus region or the entire image is one of the very common post-processing operations to correct out-of-focus photographs, or to enhance the aesthetic quality of already sharp pictures. Sharpness is related to the magnitude and frequency of the image contrast within the in-focus region. On the other hand, increasing the depth of the photograph through the use of specific camera lenses is a technique often employed by professional photographers.

The clarity rule of photographic composition states that each picture should have a clear principal idea, topic, or center of interest to which the viewer's eyes are attracted.

**b. Framework for Resolution-Preserving (Pol)(In)SAR Denoising**

This approach describe a generic framework, which is called NL-SAR [12], for nonlocal denoising of radar images. The method handles amplitude (SAR), interferometric (InSAR), polarimetric (PolSAR), or polarimetric and interferometric (PolInSAR) images in a unified way. The proposed resolution-preserving denoising method brings several novel contributions:

1) *Adaptivity to local structures*: Method automatically selects the best local estimate among several computed with different parameters, thus adapting to the scale and the contrast of local structures.

2) *Unsupervised method*: By careful weighting of covariance matrices, parameters of the model do not require any tuning related to the noise statistic. Moreover, by considering a wide variety of parameters and automatically selecting locally the best ones, the method is fully automatic.

3) *Genericity*: In contrast to approaches requiring either single-look images or multilooking, method can process single-look and multilook images without degrading the resolution prior to performing denoising.

The identification of similar pixels is performed using the full interferometric and/or polarimetric information, introducing less blur than intensity-only criteria.

4) *Robustness to noise correlation*: Side lobes of strong echoes are often reduced using spectral apodization in radar imagery. This operation correlates noise as a side effect. Current nonlocal approaches cannot be applied on correlated noise and require subsampling to decorrelate noise.

5) *Efficient implementation*: The reuse of some computations to derive estimates with different parameters and parallel implementation lead to an efficient algorithm that can be applied to large images.

**c. Anisotropic Diffusion Filter**

To avoid the influence of gradient information due to the lack of contours and low contrast of images by means of a probabilistic-driven selective filtering that preserves relevant clinical details in regions of interest due to the effect of the memory equations, two different mechanisms are formulated[13] to take advantage of the tissue characterization with the aim of preserving relevant clinical information: First includes a selective diffusion mechanism by means of the probabilistic characterization of tissues in images. Second and more important, extends the formulation to a probabilitydriven memory mechanism in order to establish different memory behaviors depending on tissues. The first one leads to a more aggressive filtering in regions with no relevant information for clinical purposes, whereas the diffusion in regions with presumable relevant information (regions with structures and textures used for diagnosis) is reduced. The second one accounts for the preservation of the structures through the diffusion process in regions of interest by leading to steady states where the undesired speckle has been removed in non relevant regions and the important structures remain visible. Both extensions considerably alleviate the problem of over-filtering present in the speckle diffusion filter paradigm because information from the beginning of the process is always taken into account in further iterations. The selective memory mechanism is established by introducing a spatial dependence on the relaxation time $\tau$ and by defining a new filtering tensor operator $S\{.\}$ that accounts for the selective preservation of tissue.

The bilateral filter is a well known edge-preserving image smoothing tool. The key idea of the bilateral filter consists in introducing a photometric weight into the standard.

Gaussian filter. The effect of this weight is to cancel spatial interactions between pixels with an important intensity difference. The bilateral filter is now used in many different applications, for instance: sharpness enhancement, upsampling, depth map refinement, image editing and fog removal.

The bilateral filter is connected to the robust estimation of the intensity average in a neighborhood. The staircase effect which may be observed in the results can be canceled by using linear fitting rather constant fitting. The bilateral filter can be extended as the adaptive bilateral filter where the scale parameter in the photometric weight is selected using the intensities of the neighbor pixels. There are several ways to improve the computation time of the bilateral filter, for instance using a grid or using distributive histograms. In some situations, information about the structure of the target image is available under the form of a similar image, called the guide image. The latter may be used to define a guide weight which may be introduced, either in place of the photometric weight (leading to the Joint/Cross bilateral filter or in conjunction with it (Dual bilateral filter).

### d. Joint Non-Gaussian Denoising and Superresolving

The wide spreads of high frame rate cameras provide us with a flexible way to capture the real world scenarios in a highly dynamic fashion. However, this attractive advantage comes at the expense of two accompanying shortcomings. First, the high frame rate videos are usually corrupted with abundant noise due to limited photons. Secondly, the high frame rate videos are usually lacking of sufficient spatial resolutions because of limited bandwidth of a video camera.

These above disadvantages largely limit their potentials for many practical applications and motivate us to raise the quality and spatial resolution of high frame rate videos. Therefore, it is quite desirable to remove the non-Gaussian noises for the high frame rate videos and meanwhile reconstruct their high resolution representations. Although neither signal-dependent-noise removal nor super resolution is a new topic, it is still quite challenging to handle these two problems simultaneously in a single task because neither denoising and super resolution is solved perfectly, so the errors in separate steps tend to accumulate in sequential optimization and accordingly affect the final performance. Therefore, design of a joint optimization framework instead of sequential or iterative optimization to produce a noise free super resolved high frame rate video sequence from its corresponding noisy low resolution version is elaborated in [4].

The bulk of the model can be explained from the following three perspectives:

1) *Temporal Low Rankness:* As known, the usual video frames (around 30 frames-per-second) are temporally redundant, and the redundancy is even greater for high frame rate videos.

2) *Spatially Sparseness:* In spatial domain, natural images can be sparsely reconstructed with an over complete dictionary and a high

resolution image can be recovered from its down sampled version.
3) *Noise Nonlinearity:* The signal dependent noise is explicitly represented using a pre-configured additive nonlinear model with parameters accounting for the range of signal dependent noise. The noise parameters are CCD specific and can be easily calibrated by off-the-shelf methods. Naturally, enhancing high frame rate videos can be performed by optimizing an objective function defined according to above observations.

**e. Spatiotemporal Video Filtering**

Digital videos may be degraded by several spatial and temporal corrupting factors which include but are not limited to noise, blurring, ringing, blocking, flickering, and other acquisition, compression or transmission artifacts. Work based on [5] focus on the joint presence of random and fixed-pattern noise (FPN). The FPN typically arises in raw images acquired by focal plane arrays (FPA), such as CMOS sensors or thermal microbolometers, where spatial and temporal nonuniformities in the response of each photodetector generate a pattern superimposed on the image approximately constant in time. The spatial correlation characterizing the noise corrupting the data acquired by such sensors invalidates the classic AWGN assumptions of independent and identically distributed (i.i.d.) –and hence white– noise. The FPN removal task is prominent in the context of long wave infrared (LWIR) thermography and hyperspectral imaging. Existing denoising methods can be classified into reference-based (also known as calibration-based) or scenebased approaches. Reference-based approaches first calibrate the FPA using (at least) two homogeneous infrared targets, having different and known temperatures, and then linearly estimate the nonuniformities of the data. However, since the FPN slowly drifts in time, the normal operations of the camera need to be periodically interrupted to update the estimate which has become obsolete. Differently, scene-based approaches are able compensate the noise directly from the acquired data, by modeling the statistical nature of the FPN; this is typically achieved by leveraging nonlocal self-similarity and/or the temporal redundancy present along the direction of motion.
A scene-based denoising framework for the joint removal of random and fixed-pattern noise based on a novel observation model featuring two spatially correlated (nonwhite) noise components have been proposed in [5]. This framework denotes as RF3D, is based on motion-compensated 3D spatiotemporal volumes characterized by local spatial and temporal correlation, and on a filter designed to sparsify such volumes in 3D spatiotemporal transform domain leveraging the redundancy of the data. Particularly, the 3D spectrum of the volume is filtered through a shrinkage operator based on a threshold array calculated from the motion trajectory of the volume and both from the individual power spectral densities (PSD) and the noise variances of the two noise components. The PSDs are assumed to be known, whereas the noise standard deviations are adaptively estimated from the noisy data.

## Conclusions

Survey paper discusses various methods for noise removal and enhancements in the image (or digital videos). Different techniques suggested by researchers including automated aesthetic analysis, Resolution-Preserving (Pol)(In)SAR Denoising, Anisotropic Diffusion Filter, Joint Non-Gaussian Denoising and Superresolving, Spatiotemporal Video Filtering are briefly elaborated.

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