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A REVIEW OF EFFICIENT REMOVAL OF NOISE FROM DIGITAL VIDEOS AND IMAGES

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Abstract:
An image and video quality enhancement is a long standing area of research. Noise is a dominant factor that degrades image and video quality. Video denoising is a challenging task in image processing. The main aim of this paper is to review an efficient, adaptive and high quality video denoising algorithms that can effectively remove real, structured noise. It is a future task to develop a model for the reduction of multiplicative noise by considering the various properties and behavior in denoising process.

Keywords: video denoising, non local means(NLM), Fixed-pattern noise (FPN), Multipicative Noise

Introduction

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, and compression or transmission artifacts. Video denoising methods can be divided into three types-

1) Spatial video denoising methods
2) Temporal video denoising methods
3) Spatial temporal video denoising method

Video denoising methods are designed and implemented for specific types of noise. Denoising is still one of the most fundamental, widely studied problems in image processing. The purpose of denoising is to retrieve and estimate the original image from noisy image data. Despite of substantial improvements in modern advanced digital cameras including resolution and sensitivity, quality of video in low light conditions is still limited. The reason behind it, a low light video have poor dynamic range. To achieve higher dynamic range, most of the consumer cameras often rely on automatic exposure control, but longer exposure time results in motion blur. Also the image sequences captured in low light conditions often have very low signal to noise ratio.

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 bolo meters, 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 task of FPN removal 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 to compensate the noise directly from the acquired data, by modeling the statistical nature of the FPN.

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 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.

Related study

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 [1], Zhenyu Zhou, ZhichangGuo, Gang Dong, Jiebao Sun, Dazhi Zhang, Boying Wu, proposed, a doubly degenerate nonlinear diffusion equation model for multiplicative noise removal.

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 built-in nonlinearity in imaging system, and the additive Gaussian white noise. By making use of structure for the objective function, an efficient alternating direction method of multipliers developed the proposed model.

S. Pizzer, e. Amburn [3] suggested an approach that constructs a structure of adaptive anisotropic image filter that is called "3D structure tensor", but this method become unstable and produces blurry results, when illumination level become very low.

C. Tomasi [4] suggested a spatio temporal connective filter and adaptive piecewise mapping function for input video. They combined local image statics into bilateral filter to form noise reduction filter but this method was not for low light video, so may not provide reliable result.

S.W. Lee, V. Maik[5] addressed the concept of noise adaptive spatio temporal filter that consider both Poison noise and false color noise of input videos. Since their method aims only to videos slightly lower than normal lighting conditions, enhancement of input dynamic range is omitted.

Bennett and McMillan [6] developed an enhancement framework for low dynamic range video based on a virtual exposure camera model. Their method includes the bilateral ASTA-filter (Adaptive Spatio-tempporal Accumulation) and tone-mapping with a logarithmic function applied to a large scale and detail features separately.

Stanley H. Chan, Todd Zickler [7], proposed a randomized version of the nonlocal means (NLM) algorithm for large-scale image filtering. The new algorithm, 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.

Francesco Conte, Alfredo Germani, and GiulioIannello [8], proposed a new method for removing noise and blurring from 3D microscopy images. The main contribution is the definition of a space-variant generating model of a 3-D signal, which is capable to stochastically describe a wide class of 3-D images. The method is able to remove, at each spatial step, both blur and noise, via a linear minimum variance recursive one-shot procedure, which does not require the simultaneous processing of the whole image. The consistency of this model, together with the linear optimality of Kalman filter, allows the method to provide a minimum variance linear estimation of the original image.

Hongyi Li, Zhengrong Zhang, Liang Xiao, Zhihui Wei [9], suggesteda three-dimensional (3-D) kernel regression hyper spectral image (HSI) denoising mechanism. They proposed a 3-D tensor diffusion matrix based kernel regression HSI denoising method.

Dai-Qiang Yin, Ying Gu, Nai-Yan Huang [10], presented a new variational model through designing a novel regularizing term based on Block Matching and 3-D filtering (BM3D), which is efficient to denoise speckled images in optical coherence Tomography (OCT). In the proposed algorithm, speckle noise is modeled as Rayleigh distribution, which is usually made additive by means of alogarithmic transformation in other digital filtering methods.

MatteoMaggioni, GiacomoBoracchi, Alessandro Foi, and Karen Egiazarian [11], reported a powerful video filtering algorithm that exploits temporal and spatial redundancy characterizing natural video sequences. The algorithm implements the paradigm of nonlocal grouping and collaborative filtering, where a higher dimensional transform-domain representation of the observations is leveraged to enforce sparsity, and thus regularize the data: 3-D spatiotemporal volumes are constructed by tracking blocks along trajectories defined by the motion vectors.

Observations of Research carried out so far

1. Multiplicative noise removal is a challenging task in image processing, in most of the existing schemes carried out the work on gray scale images and not on color images.

2. Not enough analysis is carried out by considering the various properties and behavior in denoising process.

3. In case of Joint Removal of Random and Fixed-Pattern Noise, most of the research is focused on 2D images.

Summery

Development of novel nonlinear diffusion filter denoising framework is a future task, which takes into account not only the information of the gradient of the images, but also the information of gray levels of the images. To develop a model for the reduction of multiplicative noise by considering the various properties and behavior in denoising process, it is quite desirable to remove the non-Gaussian noises for the high frame rate videos and meanwhile reconstruct their high resolution representations.

It is necessary to perform research on 3D video for Joint Removal of Random and Fixed-Pattern Noise.

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