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MUTUAL NOISE ESTIMATION ALGORITHM FOR VIDEO DENOISING

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ABSTRACT:

This project presents a novel algorithm to estimate spatio-temporal noise variance in videos. The algorithm uses mutual information from the spatial and temporal noise statistics to detect homogeneous blocks in a video frame and estimate the noise. The experimental results show the accuracy and robustness of the algorithm over videos with low to high spatial and temporal complexities, and varying levels of noise power and noise correlations.

INTRODUCTION

With today's advances in sensor design, the image/video is relatively clean for high-end digital cameras at low sensitivities, but it remains noisy for low-cost cameras at high sensitivities, e.g., low light condition, high ISO setting and high-speed rate. The problem of removing image noise is still of acute and in fact growing importance with the prevalence of webcams and mobile phone cameras. In general, video data tend to be more noisy than single image due to high-speed capturing rate of video camera. Video denoising aims at effificiently removing noise from all frames of a video by utilizing information in both spatial and temporal domains. Such an integrated approach is more optimal than independently applying a single-image denoising method on each frame of the video, as there exist high temporal redundancies in a video compared to a single image. Most existing image/video denoising techniques rely on a single statistical model of image noise, such as i.i.d. Gaussian noise, which is often violated in practice. For example, fifive major sources of image noise with different statistical distributions have been identifified in fifixed pattern noise, amplififier noise, photon shot noise, dark current noise and quantization noise. As a result, the performance of most existing denoising techniques will severely degrade when applied on those real noisy images with noises from multiple sources.

Digitalized Visual Information has gained momentum as a prominent means of communication in the present era. Whenever digitized information (data and images) is transmitted through any media, it gets corrupted with noise. Denoising an image poses a challenge to the society at large and prevails in the communities of medical, environmental, educational and in other areas. To help these communities in perseverance of their analysis, we need to provide images with enhanced quality without noise. An image without noise is the 'mantra' that has attracted researches and scholars to identify an optimum algorithm, architecture and model to get a better visually qualitative image. An exploration in the field of internet and intranet applications during the last decade has resulted in increased usage of digital images. Various methods and technologies have been identified by eminent researchers and scholars to provide images without noise, clarity and qualitative for evaluation. The advent of radiology in the field of medical research and diagnoses require large number of images with superior quality. The quality of an image is determined by presence of noise in it, pixel resolution and dimension. In the present era of digital image application requirement, there is a need to have an efficient image denoising and restoration method as these images are often taken in poor conditions. The need for image improvement cannot be compromised albeit state of the art modern equipment are deployed for capturing images. Images are ideally encoded with gray level matrix or values of colour. The dependency of image accuracy is basically on its blur and noise contents, wherein blur is an intrinsic factor based of image acquisition system have finite number of samples. For example, the image can be defined as "x" and denoising operator as "Dh" where the filtering parameter considered to be "h". This can be defined by the noise method and image difference as x- Dh x. This paper aims at developing a robust video Denoising algorithm capable of removing mixed noise from image sequences. The proposed video denoising method is built upon the same methodology "grouping and collaboratively fifiltering" as many patch-based methods do. Different from existing methods, our proposed algorithm is derived with minimal assumptions on the statistical properties of image noise. The basic idea is to convert the problem of removing noise from the stack of matched patches to a low rank matrix completion problem, which can be effificiently solved by minimizing the nuclear norm (`1 norm of all singular values) of the matrix with linear constraints. It is shown in the experiments that our low-rank matrix completion based approach can effificiently remove complex noise mixed from multiple statistical distributions.

LITERATURE SURVEY

Ajit Rajwade et al. (2011) proposed a very modest and well-designed path based machine learning technique using Higher Order Singular Value Decomposition (HOSVD) for image denoising. In this model, the similar patches are grouped together from noisy image have similarity, defined by criterion of statistically motivated 3D stack and compute HOSVD coefficients for the same. Subsequently, these coefficients are manipulated using hard thresholding method and transforming inverse of HOSVD for producing ultimate filtered image. This technique is basically applied on color images and gray scale images. It removes Gaussian noise alone and selects the optimal patch size, which is not constant across the images. Boaz Ophir et al. (2011) proposed an image denoising model based on signals represented as sparse and redundant, multi scale dictionary learning 20 paradigms i.e K-Singular Value Decomposition (K-SVD) and Wavelets. Power of learned dictionaries combined with Generic Multi-scale Representations enables capturing of signals with intrinsic characteristics. It helps to represent data in sparse manner which is more effective and looks at the signals globally.

K-SVD cannot be directly deployed on large blocks to achieve effective image denoising Hancheng Yu et al. (2009) proposed applying of Wavelet Based Trivariate Shrinkage filter with spatial based joint bilateral filter to remove Gaussian noise from corrupted images. Coefficient of wavelet domains are modeled as trivariate Gaussian distribution. Deriving trivariate shrinkage filter is possible by using “Maximum A Posteriori” Estimator, considering statistical dependencies among intra-scale wavelet coefficient. This approach provides unappreciable results for real time images. This method proposes an effective denoising algorithm for removing unwanted noise while preserving the edges by receiving two parameters from the user. The user must select the most suitable parameter values to achieve the utmost meaningful result.

Ling Shao et al. (2013) proposed an innovative model for image denoising based on reviewing and making a comprehensive comparison of algorithms from Heuristic Optimization to Dictionary learning. Through learning a large group of patches from an image dataset, this method performs denoising of images. Linear combination of

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similar patches available in redundant dictionary canbe expressed based on each patch existing in the image dataset. K-clustering with Singular Value Decomposition (K-SVD), Learned Simultaneous Sparse Coding (LSSC) and Clusteringbased Sparse Representation (CSR) methods are considered as prominent redundant dictionary based learning techniques. K-SVD method adopts the technique of searching optimal decomposition of patch in the whole image dictionary while updating the same with given input information.

EXISTING SYSTEM

Image denoising by non-local averaging

Neighborhood filters are nonlocal image and movie filters which reduce the noise by averaging similar pixels. The first object of the paper is to present a unified theory of these filters and reliable criteria to compare them to other filter classes. A CCD noise model will be presented justifying the involvement of neighborhood filters. A classification of neighborhood filters will be proposed, including classical image and movie denoising methods and discussing further a recently introduced neighborhood filter, NL-means. In order to compare denoising method three principles will be discussed. The first principle, “method noise”, specifies that only. Noise must be removed from an image. A second principle will be introduced, “noise to noise”, according to which a denoising method must transform a white noise into a white noise. Contrarily to “method noise”, this principle, which characterizes artifact-free methods, eliminates any subjectivity and can be checked by mathematical arguments and Fourier analysis.

PROPOSED SYSTEM

SOURCES OF NOISE

Noises are inevitable in images during the time of acquisition or transmission; various factors and processes are attributed to its presence in an image. The quantification of noise is decided based on the number of pixels corrupted in an image. The following factors are considered to be the prime sources for the presence of noise in an image. 3 (i) Environmental condition prevailing during image acquisition which affect the imaging sensor (ii) Noise may be introduced in an image due to insufficient levels of light and sensor temperature. (iii) An image may also be corrupted with noise due to transmission interference. (iv) Presence of dust particles in the screen scanner may also be a cause for introducing noise in an image.

DENOISING PROCESS

The process of denoising to be applied is based on an algorithm that can remove the parameters of noise in a noisy image without affecting the inherent features of the same, using various denoising methods. The major complication in this process is that it makes use of various complicated algorithms and cumbersome models that have their own advantages and disadvantages Application of wavelet provides an excellent parameter in the field of image denoising based on its characteristics like sparsity and multi-resolution structure. To cater to the need, wavelet transform has gained increased popularity in the last few decades; various algorithms have been developed in the wavelet domain as observed in published papers and articles relating to image denoising In this thesis, the best available methods have been evaluated, keeping intact the genuine characteristics of the original images in order, that they do not lose their natural inheritance. The denoising process has been evolved based on comparison of hybrid applications, their efficiency, wavelet dictionaries and image characteristics. Based on comparison, a general mathematical and experimental methodology is evolved which can help to overcome the bottlenecks of existing algorithms and methods. The denoising performances of prominent methods are compared on the basis of mathematical regression analysis and magnitude of noise.

RESULTS EXPLANATION

In this section, we evaluate the performance of the proposed method on several video samples corrupted by different types of mixed noise. All the video data used in the experiments can be downloaded from the website. By default, we use $K = 50$ image frames, set patch size to be 8×8 pixels, sample references patches with sample interval 4×4 pixels. Set the range of image intensity to [0, 255]. For each reference patch, 5 most similar patches are used in each image frame based on `1 norm distance function. Thus, totally 250 patches are stacked for the reference patch and the column dimension of the matrix in the matrix completion algorithm is 250. The threshold used in selecting reliable pixels from patch matrix is chosen to be $2\bar{\sigma}$, where $\bar{\sigma}$ is an estimation of standard deviation of noise which can be obtained in a similar way as σb. In the matrix completion algorithm, the stopping criterion is either the tolerance $\leq 10-5$ or the maximal number of iterations 30 being reached, whichever is reached first.

We applied our proposed denoising method on several videos with different mixed noise levels. The results are compared to that of two existing video denoising methods: one is the VBM3D method ([10]) using the authors' executable code from their website; the other is the PCA- based method by ([28]). it is noted that a depth constrained patch matching is used in [28] to form stacks of patches of high quality. As this paper focuses on how to denoise the stack of patches, we only implemented the denoising part of [28] and use our own patch matching algorithm to generate stacks of patches. The parameters involved in both methods are set according to the ground truth of noise levels.

Fig: Denoised Image

CONCLUSION

In this project, we propose a robust patch-based algorithm to remove mixed noise from video data. By formulating the video denoising problem to a low-rank matrix completion problem, our proposed algorithm does not assume any specific statistical properties of image noise and the robustness to patch matching errors is also built in. The effectiveness of our proposed algorithm is also validated in various experiments and our method compared favorably against two state-ofart algorithms. In future, we would like to study most robust low-rank matrix completion algorithm with respect to Poisson-type noises. Also, we are interested in investigating the extension of our work to single image denoising.

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