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# Image Deblurring with Face Detection

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**Abstract** — In many applications, like surveillance, image sequences are of the poor quality. Motion blur in particular introduces the significant image degradation. An interesting challenge is to merge many of the images into one high-quality, estimated still. We propose the method to achieve this. Firstly, an object of interest is tracked through the sequence using the region based matching. Secondly, degradation of the images is modeled in the terms of pixel sampling, defocus blur and the motion blur. Motion blur direction and the magnitude are estimated from tracked displacements. Finally, an high-resolution deblurred image is reconstructed. The approach is illustrated with the video sequences of moving people and the blurred script. Removing noise from the original signal is still an challenging job for the researchers. There have been several numbers of the published algorithms and each target to remove the noise from original signal. Discriminative model learning for the image denoising has been recently attracting considerable attentions due to its favorable denoising performance. We take one step forward by investigating the construction of the feed-forward denoising convolutional neural networks (DnCNNs) with a wavelet transform to embrace the progress in the very deep architecture, learning algorithm, and regularization method into the image denoising.

**Keywords**- Denoising Convolutional Neural Networks (DnCNNs) ,Deblurr,Gaussian denoising

## 1. INTRODUCTION

Real images of an moving object can each be regarded as a degraded representation of the ideal image that would have been captured at a certain instant by an ideal camera. These degradations includes an: (i) optical blur (ii) image sampling by the CCD array (iii) motion blur. Often changing the cameras to improve the quMity of the images is not an option, so post-processing is needed to restore the images. The aim of this paper is to recover the flow a sequence of images a higher resolution DE blurred image that is as close as possible to a ideal image, by removing the blur due to an real image formation process. Firstly, a object is tracked using the area-based deformable regions. Secondly, given an initial estimate of the ideal image, a physical image formation process is simulated. Finally the ideal image is estimated recursively by minimizing the difference between a real images and the simulated ones.

## 2. LITERATURE REVIEW

***1) Image deblurring methods and image quality evaluation***
**AUTHORS:** Vassil Guliashki1 , Dimo Dimov2
This paper surveys methods and approaches for the digital software image stabilization by a algorithmic image deblurring, so that the original form of the image is restored in the best possible way and the image is altered in an sharper, clearer state. Some techniques for the image quality evaluation are also considered.

**2)** ***Adaptive total variation image deblurring: A majorization–minimization approach***
**AUTHORS:** Joa˜o P. Oliveira , Jose´ M. Bioucas-Dias, Ma´ rio A.T. Figueiredo
This paper presents a new approach for image deconvolution (deblurring), under total variation (TV) regularization, which is adaptive in the sense that it does not require the user to specify a value of the regularization parameter.They follow the Bayesian approach of integrating out this parameter, which is achieved by using an approximation of an partition function of the Bayesian prior interpretation of a TV regularizer. The resulting optimization problem is then attacked using the majorization–minimization algorithm. Although a resulting algorithm is of the iteratively reweighted least squares (IRLS) type, thus suffering of an infamous „„singularity issue"", they show that this issue is in fact not problematic, as long as adequate initialization is used. Finally, they report experimental results showing that the proposed methodology achieves state-ofthe-art performance, on par with a TV-based methods with hand tuned regularization parameters, as well as with the best wavelet-based methods.

**3.** ***Beyond a Gaussian Denoiser: Residual Learning of Deep CNN for Image Denoising***
**AUTHORS:** Kai Zhang, Wangmeng Zuo, Senior Member, IEEE, Yunjin Chen, Deyu Meng, Member, IEEE, and Lei Zhang Senior Member, IEEE
This paper presents an ‚Discriminative model learning for the image denoising has been recently attracting considerable attentions due to its favorable denoising performance. In this paper, they take one step forward by investigating the construction of feed-forward denoising convolutional neural networks (DnCNNs) to embrace the progress in very deep

architecture, learning algorithm, and an regularization method into image denoising. Specifically, residual learning and the batch normalization are utilized to speed up the training process as well as to boost the denoising performance. Different from the existing discriminative denoising models which usually train an specific model for the additive white Gaussian noise (AWGN) at a certain noise level, our DnCNN model is able to handle the Gaussian denoising with unknown noise level (i.e., blind Gaussian denoising). With a residual learning strategy, DnCNN implicitly removes the latent clean image in the hidden layers. This property motivates us to train a single DnCNN model to tackle with the several general image denoising tasks such as Gaussian denoising, single image super-resolution and a JPEG image deblocking.Their extensive experiments demonstrate that their DnCNN model can not only exhibit high effectiveness in several general image denoising tasks, but also be efficiently implemented by benefiting from a GPU computing.

**4.** ***Image Denoising by Sparse 3-D Transform-Domain Collaborative Filtering***
**AUTHORS:** Kostadin Dabov, Student Member, IEEE, Alessandro Foi, Vladimir Katkovnik, and Karen Egiazarian, Senior Member,
IEEE
This paper experiments on an novel image denoising strategy based on an enhanced sparse representation in the transform domain. The enhancement of the sparsity is achieved by grouping the similar 2-D image fragments (e.g., blocks) into 3-D data arrays which we call "groups." Collaborative filtering is the special procedure developed to deal with these 3-D groups. They realize it using a three successive steps: 3-D transformation of a group, shrinkage of the transform spectrum, and the inverse 3-D transformation. The result is the 3-D estimate that consists of the jointly filtered grouped image blocks. By attenuating the noise, an collaborative filtering reveals even the finest details shared by grouped blocks and, at the same time, it preserves the essential unique features of each individual block. A filtered blocks are then returned to their original positions. Because these blocks are overlapping, for each pixel, they obtain many of different estimates which need to be combined. Aggregation is the particular averaging procedure which is exploited to take advantage of this redundancy. The significant improvement is obtained by a specially developed collaborative Wiener filtering. An algorithm based on this novel denoising strategy and its efficient implementation are presented in detail; an extension to color-image denoising is also developed. The experimental results demonstrate that this computationally scalable algorithm achieves a state-of-the-art denoising performance in terms of both peak signal-to-noise ratio and subjective visual quality.

**5.** ***Nonlocal Image and Movie Denoising***
**AUTHORS** : Antoni Buades , Jean-Michel Morel ,Bartomeu Coll ,
In this paper, the Neighborhood filters are nonlocal image and movie filters which reduce the noise by averaging similar pixels. The first object of a 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 a neighborhood filters. A classification of the neighborhood filters will be proposed, including a classical image and movie denoising methods and discussing further a recently introduced neighborhood filter, NL-means. In order to compare DE noising methods three principals will be discussed. The first principle, "method noise", specifies that only the noise must be removed from an image. A second principle will be introduced ,like "noise to noise", according to which the denoising method must transform an white noise into a white noise. Contrarily to "method noise", this principle, which characterizes the artifact-free methods, eliminates any subjectivity and can be checked by the mathematical arguments and Fourier analysis. This is why the third and new comparison principle, the "statistical optimality", is needed and will be introduced to compare a performance of all neighborhood filters. The three principals will be applied to compare the ten different image and movie denoising methods. It will be first shown that only a wavelet thresholding methods and the NLmeans give an acceptable method noise. Second, that the neighborhood filters are the only ones to satisfy the "noise to noise" principle. Third, that among them NL-means is closest to the statistical optimality. A particular attention will be paid to an application of a statistical optimality criterion for the movie denoising methods. It will be pointed out that current movie denoising methods are a motion compensated neighborhood filters. This amounts to say that they are neighborhood filters and that the ideal neighborhood of the pixel is its trajectory. Unfortunately a aperture problem makes it impossible to estimate the ground true trajectories. It will be demonstrated that the computing trajectories and restricting the neighborhood to them is harmful for denoising purposes and that space-time NL-means preserves more movie details.

## 3. EXISTING SYSTEM

Image denoising is the classical yet still active topic in the low level vision since it is an indispensable step in a many practical applications. The goal of image denoising is to recover a clean image x from the noisy observation y which follows an image degradation model y = x + v. One common assumption is that v is the additive white Gaussian noise (AWGN) with standard deviation
σ. There are various models have been developed, but they having some drawbacks.

## 4. PROPOSED SYSTEM

We propose an end-to-end trainable deep CNN for the Gaussian denoising. In contrast to the existing deep neural network-based methods which a directly estimate the latent clean image, a network use wavelet transform to remove noise. Our DnCNN can be easily extended to handle the general image denoising tasks. We can train a single DnCNN model for the blind Gaussian denoising, and achieve the better performance than the competing methods trained for a specific noise level.

**Advantages of Proposed System:**

We can perform the comparison as well as the data encryption back encryption back side of image.

We can easily hide the large amount of a data background of image.

## 5. SYSTEM ARCHITECTURE

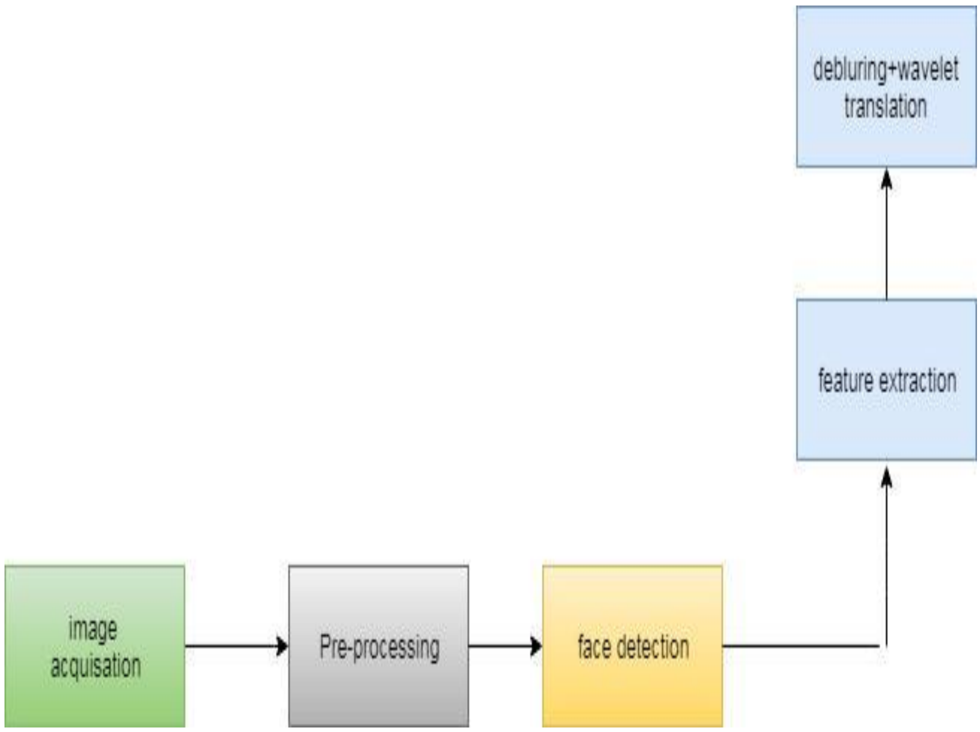


Fig.: System Architecture

## 6. CONCLUSION AND FUTURE WORK

It combines the deep convolution neural network with a directional wavelet approach. We demonstrated that the proposed method has a greater de-noising power. Its reconstruction time is much faster than the other methods. We believe that the method presented here suggests an new innovative framework. We will investigate an proper CNN models for denoising of an images with the real complex noise and an other general image restoration tasks.

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