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STATISTICAL NEAREST NEIGHBORS FOR IMAGE DENOISING

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Abstract:

Image Denoising plays vital role in digital image processing. The purpose of image denoising is to remove noise from any digital image. Any digital image is comprised of pixels of different size of matrices. Various Image Restoration algorithms have been developed. In this paper, we have compared pixels of two different images one, the original image and the other, the degraded image. Once we get the difference between the two pixels which can be called as the added noise then we have subtracted that noise from the degraded image. In this way the original image can be restored from the degraded image. For denoise we implemented Support Vector Machine Algorithm for speed and accuracy.

Keywords — **Support Vector Machine, Denoise, Matrices, Resat oration Algorithm, Machine Learning,**

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I. INTRODUCTION

Self-similarity driven algorithms are based on the assumption that, for any patch in a natural image, replicas of the same patch exist within the image and can be employed, among other applications, for effective denoising. Since processing uses non-local (NL) information, these algorithms are commonly referred to as NL algorithms. Non-Local-Means (NLM), one of the most well-known denoising algorithms, has been widely investigated by researchers. It is conceptually simple: denoising of a given patch is obtained as a weighted average of the surrounding patches, with weights proportional to the patch similarity. Several authors analyzed the complex relation between the filtering parameters and the quality of the output images, whereas others concentrated their attention on reducing the computational burden of the filter to make it useful in practical applications. A widely used practice is to reduce the number of neighbors collected for each reference patch: noticeably, the 3D Block-Matching (BM3D) denoising filter achieves state-of-the-art results in this way. The neighbors' set is collected through a Nearest-Neighbors (NN) approach, which can be efficiently (although in an approximate manner), implemented. Reducing the number of neighbors leads to images with sharp edges, but it also introduces lowfrequency artifacts, clearly visible for instance in Fig. 1. Resorting to a toy problem, we show that this artifact occurs because the estimate of the noise-free patch from the set of NNs is biased towards the noisy reference patch. To the best of our knowledge, this is the first time that the neighbor collection strategy is explicitly investigated in detail as a potential source I. Frosio and J. Kautz are with NVIDIA, USA. Email: {ifrosio, jkautz}@nvidia.com. Manuscript received Aug 2017; revised Mar, 2018. Of bias, although other authors identified and tried reducing it through different weighting schemes, analyzed it

in relation to the size of the local search window, or in the context of internal external denoising; other types of bias were also analyzed in the past. Here we propose an alternative strategy to collect neighbors, named Statistical NN (SNN), which reduces the prediction error of the estimate of the noise-free patch. When filtering real images, SNN tends to blur low-contrast image details with a low signal-to-noise ratio more than NN; we explain this drawback of SNN resorting to our toy problem to analyze the differences between NN and SNN from a statistically grounded point of view, and show that a compromise between the NN and SNN strategies is easily found in practice. Our analysis and experimental results, show that, using fewer neighbors, SNN leads to an improvement in the perceived image quality, as measured by several image quality metrics on a standard image dataset, both in case of white and colored Gaussian noise. In the latter case, visual inspection reveals that NLM with SNN achieves an image quality comparable to the state-of-the-art, at a much lower computational cost. We finally show that the intuition behind SNN is indeed quite general, and it can be applied to bilateral filtering, also leading to an image quality improvement.

2. LITERATURE REVIEW.

In this paper, we present a brushlet-based block matching 3D (BM3D) method to collaboratively denoise ultrasound images. Through dividing image into multiple blocks, we group them based on similarity. Then, grouped blocks sharing similarity form a 3D image volume. For each volume, brushlet thresholding is applied to remove noise in the frequency domain. Upon completion of individual filtering, the volumes are aggregated and reconstructed globally. To evaluate our method, we run our denoising scheme on synthetic images corrupted with additive or multiplicative noise. The results show that our method can achieve good denoising performance in comparison with existing methods. Our method is also evaluated on cardiac and fetal ultrasound images. Analysis on the contrast and homogeneity of the denoised images demonstrates the feasibility of applying our method to ultrasound images to improve image quality and facilitate further processing such as segmentation.

In order to remove the complex and severe noise from sonar image more effectively, an image denoising approach based on sparse representation is carried out in this paper. Tno decompose and then reconstruct the sonar image on DCT dictionary with OMP is effective for additive noise removing. Then a logarithmic transformation was applied on the previous reconstructed image to make it adapt to sparse representation denoising model. Experiments are provided to demonstrate the performance of the proposed approach. Results show that this method is efficient in removing additive and multiplicative noise from the sonar image and is also particularly appealing in terms of both denoising effect and keeping details.

3. MACHINE LEARNING

Machine learning (ML) is the study of computer algorithms that improve automatically through experience. It is seen as a subset of artificial intelligence. Machine learning algorithms build a model based on sample data, known as "training data", in order to make predictions or decisions without being explicitly programmed to do so. Machine learning algorithms are used in a wide variety of applications, such as email filtering and computer vision, where it is difficult or unfeasible to develop conventional algorithms to perform the needed tasks.

A subset of machine learning is closely related to computational statistics, which focuses on making predictions using computers; but not all machine learning is statistical learning. The study of mathematical optimization delivers methods, theory and application domains to the field of machine learning. Data mining is a related field of study, focusing on exploratory data analysis through unsupervised learning. In its application across business problems, machine learning is also referred to as predictive analytics.

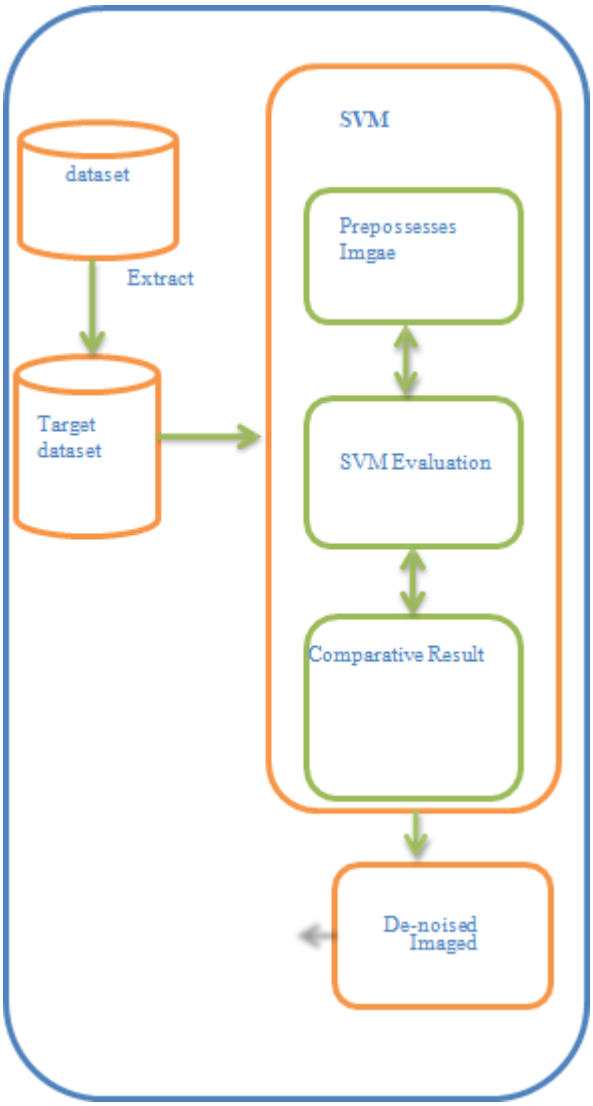
4. EXISTING SYSTEM

Primary complexity in image processing is to curb the noise in degraded image. Initially a spatial domain approach has been implemented. One of the major benefits of this filter domain

approach is that this approach is fast. However, the limitation of this approach is it was incapable to conserve edges, which are recognized as discontinuities in the image, alternatively wavelet domain technique having a immense benefit of conserving edges, was introduced later on. This approach becomes more popular for denoising of images. Various algorithm for denoising in wavelet domain were implemented subsequently it was observed that substantial enhancements in perceptual quality could be achieved by translation invariant algorithms based on thresholding of an Undecimated Wavelet Transform. Multi wavelets were also utilized to attain identical outcomes. To minimize the artifacts these thresholding approaches were applied to non orthogonal wavelet coefficients.

5. PROPOSED SYSTEM

We have developed an algorithm that will not only restore the original image; it will also keep the image quality of the original image. We have degraded the original image with the help of some added noise like “salt & Pepper noise”,”Gaussian noise”, then we has compared the image matrices of two images on pixel by pixel basis. Once we get the error between the two pixels we subtracted that error from the degraded image pixel matrix. For the computation of the error matrix, we have to keep in mind that which pixel is larger and that larger pixel has to be subtracted from the smaller pixel.



6. METHODOLOGY

A.PREPROCESSING

The **histogram of oriented gradients (HOG)** is a feature descriptor used in computer vision and image processing for the purpose of object detection. The technique counts occurrences of gradient orientation in localized portions of an image. This method is similar to that of edge orientation histograms, scale-invariant feature transform descriptors, and shape contexts, but differs in that it is computed on a dense grid of uniformly spaced cells and uses overlapping local contrast normalization for improved accuracy.

B. FEATURE EXTRACTION

Feature Extraction is applied to both training and testing images. It is used to extract the features of image. Feature Extraction is done using PCA Algorithm. PCA is used in Face recognition and activity detection for finding patterns. Eigen approach is a principal component analysis method which is used to describe the variation between face images. Eigen faces approach is used due to its simplicity, speed and learning capability. Using Eigen activity method, the images are represented as vectors instead of using Matrix representation.

C. FEATURE DOWNSAMPLING

Downsampling operations are adopted multiple times to progressively increase the receptive field of the following convolution kernels and to reduce the computation cost by decreasing the feature map size. The larger receptive field enables the kernels to incorporate larger spatial context for denoising. We use 2 as the downsampling and upsampling factors, and try two schemes for downsampling in the experiments: (1) max pooling with stride of 2; (2) conducting convolutions with stride of 2. Both of them achieve similar denoisng performance in practice, so we use the second scheme in the rest experiments for computation efficiency.

D.FEATURE UPSAMPLING

Upsampling operations are implemented by deconvolution with 4 × 4 kernels, which aim to expand the feature map to the same spatial size as the previous scale. Since all the operations in our proposed denoising network are spatially invariant, it has the merit of handling input images of arbitrary size.

7. CONCLUSION

In Recent years, we have seen after going through different research paper that no algorithm is suitable for all types of noises. One Algorithm that is suitable for one set of noise may not be suitable for another set of noise. However, in this paper, we have compared different algorithms and obtained the different restored images. We found that this algorithm is applicable for all kind of noises. This algorithm will not only suppress the noise to a larger extent, it also preserves the sharpness of the image.

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