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GLOBAL IMAGE DENOISING ENHANCED WITH TV AR NL-MEANS ALGORITHM

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ABSTRACT

Image denoising is one of the fundamental problems in image processing. Here developed a technique for global filtering, where each pixel is estimated from all pixels in the image. The system uses Nystrom extension for statistical analysis. The nonlocal means (NL-means) perform denoising by exploiting the natural redundancy of patterns inside an image, then perform a weighted average of pixels whose neighborhoods (patches) are close to each other The regularized NL-means algorithm combines these methods and reduces both of their respective defaults by minimizing an adaptive total variation with a nonlocal data fidelity term. Besides, this model adapts to different noise statistics and a fast solution can be obtained in the general case of the exponential family Peak signal to noise ratio (PSNR) of the image is calculated and compared with the median filter. Canny edge detector, an edge detector that uses a multi stage algorithm to detect a wide range of edges in image with MATLAB tool. This method achieves better structural similarity performance and provides better visual quality.

Keywords:GLIDE,TV,AR,NL-Means,Nystrom extension, Prefiltering, sampling, optimal filter.

1. INTRODUCTION

In image processing, noise reduction and restoration of image is expected to improve the qualitative inspection of an image and the performance criteria of quantitative image analysis techniques Digital image is inclined to a variety of noise which affects the quality of image. The main purpose of de-noising the image is to restore the detail of original image as much as possible. The criteria of the noise removal problem depends on the noise type by which the image is corrupting .In the field of reducing the image noise several type of linear and non-linear filtering techniques have been proposed. Different approaches for reduction of noise and image enhancement have been considered, each of which has their own limitation and advantages.

Digital Image Processing is a component of digital signal processing .The area of digital image processing refers to dealing with digital images by means of a digital computer. Digital image processing has several advantages above analog image processing; it allows a considerably wider collection of algorithms to be apply to input data and can keep away from problems for instance the build-up of noise and signal deformation during processing. Digital Image Processing involves the modification of digital data for improving the image qualities with the aid of computer. The processing helps in maximize the clarity, sharpness of image and details of features of interest towards extraction of information & further analysis.

Digital image processing involves the procedures which can be complex mathematically, but the central idea behind digital image processing is simple. The digital image is given as input into a computer and computer is programmed to change these data with the help of an equation, or with series of equations and then store the values of the computation for each pixel or picture element. The results form a new digital image that may be display or it can be recorded in pictorial format or it may itself be further changed by additional computer programs. To enhance certain features in the data and to remove noise from image, the digital data is subjected to different image processing operations. Noise is introduced in the image at the time of image acquisition or transmission. Different factors may be responsible for introduction of noise in the image the quantification of the corresponding effect.

1.1 Noise

Noise is a random variation of image Intensity and visible as grains in the image. It may arise in the image as effects of basic physics-like photon nature of light or thermal energy of heat inside the image sensors. It may produce at the time of capturing or image transmission. Noise means, the pixels in the image show different intensity values instead of true pixel values. Noise removal algorithm is the process of removing or reducing the noise from the image. The noise removal algorithms reduce or remove the visibility of noise by smoothing the entire image leaving areas near contrast boundaries. But these methods can obscure fine, low contrast details. Different noises have their own characteristics which make them distinguishable from others. Image noise is random (not present in the object imaged) variation of brightness or colour information in images, and is usually an aspect of electronic noise. It can be produced by the sensor and circuitry of a scanner or digital camera. Image noise can also originate in film grain and in the unavoidable shot noise of an ideal photon detector.

Image noise is an undesirable by-product of image capture that adds spurious and extraneous information. The original meaning of "noise" was and remains "unwanted signal"; unwanted electrical fluctuations in signals received by AM radios caused audible acoustic noise (static). By analogy unwanted electrical fluctuations themselves came to be known as "noise". Image noise is of course inaudible. The magnitude of image noise can range from almost imperceptible specks on a digital photograph taken in good light, topical and radio astronomical images that are almost entirely noise, from which a small amount of information can be derived by sophisticated processing (a noise level that would be totally unacceptable in a photograph since it would be impossible to determine even what the subject was). The common types of noise that arises in the image are impulse noise, additive noise and multiplicative noise etc..

1.2 Kernel Function

Kernel function is a small matrix, or mask is a small matrix useful for blurring, sharpening, embossing, edge-detection, and more. This is accomplished by means of convolution between a kernel and an image. Depending on the element values, a kernel can cause a wide range of effects. The above are just a few examples of effects achievable by involving kernels and images. Dividing each element in the kernel by the sum of all the absolute values of the elements in the kernel diagonals. Normalization ensures that the pixel values in the output image are of the same relative magnitude as those in the input image. The code so critical as that of the kernel is usually loaded into a protected area of memory, which prevents it from being overwritten by other, less frequently used parts of the operating system or by applications. The kernel performs its tasks, such as executing processes and handling interrupts, in kernel space, whereas everything a user normally does, such as writing text in a text editor or running programs in a GUI (graphical user interface), is done in user space.

1.3 Approximated error

Approximate error is a type of error in which the quantization residual is distributed to neighboring pixels that have not yet been processed. Its main use is to convert a multi-level image into a binary image, though it has other applications. Approximate error is classified as an area operation, because what the algorithm does at one location influences what happens at other locations. This means buffering is required, and complicates parallel processing. Point operations, such as ordered filter, do not have these complications. Approximate error has the tendency to enhance edges in an image

1.4 Total Variation (TV)

Total variation denoising, also known as total variation regularization is a process, most often used in digital image processing, that has applications in noise removal. It is based on the principle that signals with excessive and possibly spurious detail have high total variation, that is, the integral of the absolute gradient of the signal is high. According to this principle, reducing the total variation of the signal subject to it being a close match to the original signal, removes unwanted detail whilst preserving important details such as edges.

1.5 Adaptive regulation (AR)

Adaptive regulation has been applied widely as an advanced method compared with standard median filtering. The Adaptive regulation performs spatial processing to determine which pixels in an image have been affected by impulse noise. The Adaptive regulation classifies pixels as noise by comparing each pixel in the image to its surrounding neighbour pixels. The size of the neighbourhood is adjustable, as well as the threshold for the comparison. A pixel that is different from a majority of its neighbours, as well as being not structurally aligned with those pixels to which it is similar, is labelled as impulse noise. These noise pixels are then replaced by the median pixel value of the pixels in the neighbourhood that have passed the noise labelling test.

1.6 Structural Similarity (SSIM)

Perceptual image quality Assessment (IQA) and sparse signal representation have recently emerged as high-impact research topics in the field of image processing. Here make one of the first attempts to incorporate the structural similarity (SSIM) index, a promising IQA measure, into the framework of optimal sparse signal representation and approximation. In particular, introduce a novel image denoising scheme where a modified orthogonal matching pursuit algorithm is proposed for finding the best sparse coefficient vector in maximum SSIM sense for a given set of linearly independent atoms. Furthermore, a gradient descent algorithm is developed to achieve SSIM optimal compromise in combining the input and sparse dictionary reconstructed images. Experimental results show that the proposed method achieves better SSIM performance and provide better visual quality than least square optimal de-noising methods.

2. GLIDE

GLIDE means Global Image Denoising. The performance of algorithm is compared to state-of-the-art denoising methods for some benchmark images. Selected NLM as baseline kernel; however, any other non-local kernel could also be used. Pixel samples of the NYSTROM extension are uniformly selected and the sampling rate is set as 1% (p = n 100) and is kept fixed throughout the experiments.

Both edges and smooth features of the image are preserved better than the other methods. In the next set of experiments show that, the prefiltered images are obtained from BM3D. This method can improve upon BM3D especially at high noise levels and for images with semi stochastic textures which contain relatively few similar patches. Denoising results of the Mandrill and Monarch images for BM3D and the globalized BM3D are compared. As can be seen, the proposed method can bootstrap the performance of BM3D. In this set of experiments the best results are optimized using the no reference quality metric in performance of the proposed method for improving the NLM filter. Here also compare our results to the commercial Neat Image denoising software. As can be seen, our result is competitive to the commercial state of the art denoising.

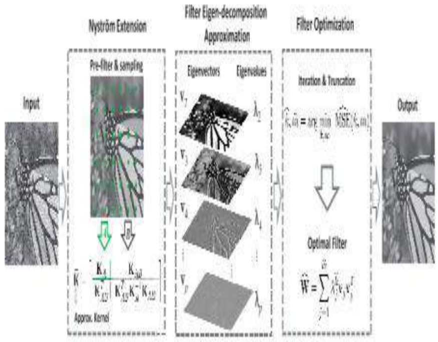

Figure 2.1:GLIDE's pipeline

From figure 7.1 left to right, for a noisy image first apply a pre-filter to reduce the error level. Using a spatially uniform sampling, the global kernel is approximated by employing the Nystrom extension (A and B represent the samples and the rest of the pixels in the image, respectively).Using the attain kernel, that leading eigenvalues and eigenvectors of the filter are approximated (The eigenvector is not shown because it is constant). At last, the optimal filter is constructed by shrinking (iteration and truncation) the eigenvalues.

2.1 Enhanced GLIDE

Image denoising is a central problem in image processing. Here used an image denoising algorithm is Total Variation Adaptive Regulation Non Local Means (TVAR-NLM) Algorithm. It is often a necessary step prior to higher level analysis such as segmentation, reconstruction, or super resolution. The nonlocal means (NL-means) perform denoising by exploiting the natural redundancy of patterns inside an image, they perform a weighted average of pixels whose neighbourhoods (patches) are close to each other.

Noise reduces significantly while preserving most of the image content. While it performs well on flat areas and textures, it suffers from two opposite drawbacks: it might over-smooth low contrasted areas or leave a residual noise around edges and singular structures. Denoising can also be performed by total variation minimization process which leads to restore regular images, but it is prone to textures, stair casing effects, and contrast losses. Here introduce in this paper a variational approach that corrects the over smoothing and reduces the residual noise of the NL-means by adaptively regularizing nonlocal methods with the total variation. The proposed regularized NL-means algorithm combines these methods and reduces both of their respective defaults by minimizing an adaptive total variation with a nonlocal data fidelity term. Besides, this model adapts to different noise statistics and a fast solution can be obtained in the general case of the exponential family. Develop this model for image denoising and adapt it to image denoising with patches.

Image denoising have necessary step prior to higher level analysis such as segmentation, reconstruction from a degraded version. Among the main denoising techniques, variational methods minimize an energy that constrains the solution to be regular. One of the most famous variational models used for image denoising is the Rudin, Osher and Fatemi (ROF) model that minimizes the total variation (TV) of the image, hence pushing the image towards a piecewise constant solution. This method is quite adapted to denoising while preserving edges, but it presents three major drawbacks the textures tend to be overly smoothed, the flat areas are approximated by a piecewise constant surface resulting in a stair casing effect, and the image suffers from losses of contrast.

3. Results and Discussion

Global image denoising enhanced with TV AR NL-Means Algorithm is described has been simulated using MATLAB version 7.8.0 (R2009a). The noise level have been reduced by using TV AR NL-Means algorithm. Which is one of the statistical methods used to detect outlier effect from a dataset. The essential advantage of applying algorithm is to preserve edge sharpness better of the orginal image and PSNR and SSIM was calculated.

The denoising approach have presented is based on a two-step improvement of on local methods. It consists in correcting the jittering effect that occurs if candidates issued from a different underlying value are averaged together (this happens for example on the grass of the cameraman, see figure 8), and in reducing the rare patch effect. Since these drawbacks are linked to the difficulty to compute the nonlocal weights on noisy patches and to find relevant candidates, are inherent to nonlocal methods. In this method uses the local estimation of the noise variance reduction as an indicator to correct first the jittering effect then the rare patch effect. Then can extend the model developed for the NL-means to other nonlocal methods based on the computation of nonlocal weights, for example BM3D, or the improved version of the nonlocal means SAFIR and SAIF. The residual variance of the nonlocal solution, that use to perform the dejittering step then the regularization step. Fig. 8 displays the result of denoising of Gaussian noise using BM3D, SAFIR and SAIF, along with the associated regularized versions using the dejittering and adaptive regularization steps. The over-smoothing of fine structures such as the grass on “cameraman” and the straw on “man” is corrected, and that some artifacts (around the tower) are reduced. Besides, thanks to the adaptivity of approach, when no jittering or rare patch effect has occurred.

4. Outputs

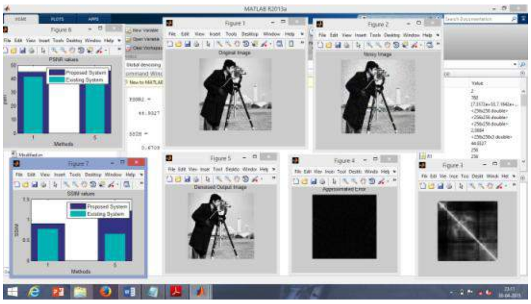

Figure 4.1: Overall output in Cameraman image

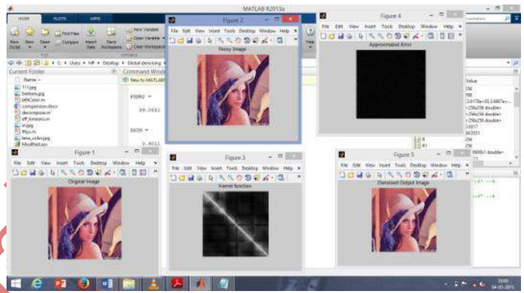

Figure 4.1: Overall output in Lena image

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