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Optimal Denoising Of an Image Using Anscombe Transformation Based Image Stabilization

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Abstract- This paper proposes an effective inversing of the anscombe transformation with the help of adaptive bilateral image denoising algorithm. The Poisson noise removal is carried out into three steps. They are First, Image pre-processin,. Second, image denoising and Third, Image retrieval. In image pre-processing the images of any format can be got as input they are then converted into gray scale images for ease of functions and this paper uses anscombe transform to stabilize the image to a constant intensity level. This is very helpful in determining the noise at low counts. For image denoising, Multiscale variance stabilizing transform is the technique that is proposed to denoise the image. Now the noisy pixels in the images are removed. This paper also proposes a similar neighborhood function that is essential for filling the noisy pixels with the help of non-local means of similar neighbors. This is suitable for overall adjustment of the image. But in the case of texture images this technique is not applicable and in that condition the technique proposed is bilateral transformation of texture images. For this we use Bilateral image denoising and PCA analysis. This paper also proposes an approach to determine the best among the two processes in terms of performance and efficiency. Next step is very crucial because the application of inverse transformation is an critical factor. The inverse transform that is proposed in this paper is minimum mean square error method. This results in retrieval of an image with efficient filtering and inversing functions.

Keywords- Anscombe transform, MS-VST, Bilateral denoising, PCA analysis, MMSE

I. INTRODUCTION

Poisson noise is characteristic of many image acquisition modalities, and its removal is of fundamental importance for many applications and particularly in astronomy and medical imaging. As the noise variance equals the expected value of the underlying true signal, Poisson noise is signal dependent, which makes the premise for Poisson denoising very different from the case of additive white Gaussian noise with constant variance typically assumed by signal processing filters. Although denoising algorithms specifically designed for Poisson noise have been proposed, often the removal of Poisson noise is performed through the followingthree-step procedure. First, the noise variance is stabilized by applying the Anscombe root transformation to the data.

This produces a signal in which the noise can be treated as additive Gaussian with unitary variance. Second, the noise is removed using a conventional denoising algorithm for additive white Gaussian noise. Third, an inverse transformation is applied to the denoised signal, obtaining the estimate of the signal of interest. This paper focuses on this last step and aims at identifying and emphasizing the role that the inversion plays in ensuring the success of the whole procedure In the recent years, variance stabilization has often been questioned as a viable method for Poisson noise removal because of the poor numerical results achieved at the low-count regime, i.e., for low-intensity signals.

We show that this disappointing performance, reported in many earlier works, is not due to the stabilization itself (i.e., to the forward transformation), but rather to the inverse transformation. The choice of the proper inverse transformation is crucial in order to minimize the bias error which arises when the nonlinear forward transformation is applied. Both the algebraic inverse and the asymptotically unbiased inverse proposed by Anscombe lead to a significant bias at low counts. In particular, the latter inverse provides unbiasedness only asymptotically for large counts while at low counts it leads to a larger bias than the former one.

II. RELATED WORK

In order to denoise Poisson count data, initially a variance stabilizing transform (VST) applied on a filtered discrete Poisson process, yielding near Gaussian process with a symptotic constant variance was used. This new transform, which can be deemed as an extension of the Anscombe transform to filtered data, is simple, fast, and efficient in (very) low-count situations. Single VST is applied it does not apply in detecting feature with different morphologies. Analyzing Poisson processes with photon limited imaging. Contributions include, Expectations maximization algorithm for ML. Extension of method to work under HMT model. Exploration of 2D recursive quad tree image representation. A multistage image representation termed as Poisson haar (PH-HMT) for better yield. This method is not applicable to problems. When single MS-VST is applied it does not apply in detecting feature with different morphologies such as image feature detection and segmentation under low light conditions.

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This method is not applicable to problems such as image feature detection and segmentation under low light conditions the problem of optimizing the parameters for restoration is considered here. So a Stein's unbiased risk estimate (SURE) which provides. A means of assessing the true mean-squared error (MSE) purely from the measured data without need for any knowledge about the noise-free signal is proposed. Monte carlo method for calculating SURE is presented. The original nonlocal means method replaces a noisy pixel by the weighted average of pixels with related surrounding neighborhoods. This method is computationally impractical. So, we introduce filters that eliminate unrelated neighborhoods from the weighted average. Used when computational complexity arises.

III. PROPOSED WORK

Combining VST with the filter bank of wavelets, ridgelets and curvelets, lead to multiscale VSTs (MS-VSTs) and non linear decomposition schemes. By doing so, the noise-contaminated coefficients of these MS-VST-modified transforms are asymptotically normally distributed with known variances. A classical hypothesis-testing framework is adopted to detect the significant coefficients, and a sparsity-driven iterative scheme reconstructs properly the final estimate. A range of examples show the power of this MS-VST approach for recovering important structures of various morphologies in (very)low-count images. These results also demonstrate that the MS-VST approach is competitive relative to many existing denoising methods. At low counts exact unbiased inverse produce significant improvement over asymptotically unbiased inverse. The problem of optimizing the parameters for restoration is considered here.So a Stein's unbiased risk estimate (SURE) which providesa means of assessing the true minimum mean-squared error (MSE) purelyfrom the measured data without need for any knowledge aboutthe noise-free signal is proposed.

A. *Image Pre-Processing*

The image pre-processing is carried out in three steps

- Image acquisition
- Image conversion
- Image stabilization

1) *Image Acquistion*: Import an image with an optical scanner or directly through digital photography. Image can be of extensions such as .jpeg, .tiff, .png, .jpg, etc.,

2) *Image Conversion:* Images of any format are transformed into gray scale image for making the denoising process simple. This process is generally carried out through some pre-defined functions in the interactive definition language. It converts any form of the image to gray scale format because the pixel definitions are simpler in the case of gray scale images when compared to that of the RGB images.

3) *Image Transformation:* The rationale behind applying a variance-stabilizing transformation is to remove the data dependence of the noise variance, Moreover, if the transformation is also normalizing (i.e., it results in a Gaussian noise distribution), we can estimate the intensity values with a conventional denoising method designed for additive white Gaussian noise. Moreover, if the transformation is also normalizing (i.e., it results in a Gaussian noise distribution), we can estimate the intensity values with a conventional denoising method designed for additive white Gaussian noise data At this stage the image is normalized. For this we use anscombe transformation. Anscombe transformation is used for Poisson noise removal at low counts.

The denoising of F (Z) produces a signal D that can be considered as an estimate of E{F(Z)|Y}. When anscombe transform is applied it stabilizes the image to a constant intensity. The noise with high counts is easily detectable but the low count noises cannot be and for that we use this transform.

B. *Image Denoising*

The Poisson noise removal method used is MS-VST. We combine VST with filters of wavelets, curvelets and ridgelets leading to MS-VST. VST is applied to remove data dependence of noise variance. Wavelets are used to represent regular structures. Ridgelets are to present global lines. Curvelets are suitable for smooth images. MS-VST is used instead of single VST because it is not suitable in feature detection with different morphologies. At this point the noisy pixels are removed. The original nonlocal means method replaces a noisy pixel by the weighted average of pixels with related surrounding neighborhoods. This method is computationally impractical. So, we introduce filters that eliminate unrelated neighborhoods from the weighted average. Using this method the areas with the noisy pixels are covered with the information from the neighboring pixels.

1) *Bilateral Filters For Denoising:* A bilateral filter is an edge-preserving and noise reducingsmoothing filter. The intensity value at each pixel in an image is replaced by a weighted average of intensity values from nearby pixels. This weight is based on a Gaussian distribution. Crucially the weights depend not only on Euclidean distance but also on the radiometric differences (differences in the range, e.g. color intensity). This preserves sharp edges by systematically looping through each pixel and according weights to the adjacent pixels accordingly

2) *Principle Component Analysis*: Principal component analysis (PCA) is a mathematical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables. This transformation is defined in such a way that the first principal component has as high a variance as possible (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it be orthogonal to (uncorrelated with) the preceding components.

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Principal components are guaranteed to be independent only if the data set is jointly normally distributed. PCA is sensitive to the relative scaling of the original variables.

PCA is the simplest of the true eigenvector-based multivariate analyses. Often, its operation can be thought of as revealing the internal structure of the data in a way which best explains the variance in the data. If a multivariate dataset is visualised as a set of coordinates in a high-dimensional data space (1 axis per variable), PCA can supply the user with a lower-dimensional picture, a "shadow" of this object when viewed from its (in some sense) most informative viewpoint. This is done by using only the first few principal components so that the dimensionality of the transformed data is reduced. PCA is closely related to factor analysis. PCA is mathematically definedas an orthogonallinear transformation that transforms the data to a new coordinate system such that the greatest variance by any projection of the data comes to lie on the first coordinate (called the first principal component), the second greatest variance on the second coordinate, and so on. Define a data matrix, X^T, with zero empirical mean (the empirical (sample) mean of the distribution has been subtracted from the data set), where each of the n rows represents a different repetition of the experiment, and each of the m columns gives a particular kind of datum. (Note that X^T is defined here and not Xitself, and what we are calling X^T is often alternatively denoted as X itself in the literature.) The singular value decomposition of X is $X = W \sum V^T$, where the m × m matrix W is the matrix of eigenvectors of XX^T, the matrix Σ is an m × nrectangular diagonal matrix with nonnegative real numbers on the diagonal, and the n × n matrix V is the matrix of eigenvectors of $X^T X$. The PCA transformation that preserves dimensionality (that is, gives the same number of principal components as original variables) is then given by:

$$\begin{aligned} Y^T &= X^T W \\ &= V \sum{}^T W^T W \\ &= V \sum{}^T \end{aligned} \tag{1}$$

The matrix W of singular vectors of X is equivalently the matrix W of eigenvectors of the matrix of observed covariances

$$XX^T = W \sum \sum{}^T W^T \tag{2}$$

From the above discussions the paper defines that the use of PCA for denoising is best both in terms of performance as well as efficiency.

C. Inverse Transformation

Once a image is transformed it is to be brought to its original form. In this case we have used anscombe transformation for stabilization and the same cannot be used for inversing because it may cause some other problems.This is a serious issue that is focused in this project. The inversing algorithm used is MMSE.The problem of optimizing the parameters for restoration is considered here. MMSE describes the approach which minimizes the MSE as a common measure of quality estimation. So a Stein's unbiased risk estimate (SURE) which provides a means of assessing the true mean-squared error (MSE) purely from the measured data without need for any knowledge about the noise-free signal is proposed.

MMSE Inverse: We define the MMSE inverse, which is parametrized by ε, as

$$\begin{aligned} I_{MMSE}(D,\varepsilon) &= \arg\min_{\hat{y}} E\{(y-\hat{y})^2 \mid D\} \\ &= \arg\min_{\hat{y}} \int_{-\infty}^{\infty} p(y \mid D)(y-\hat{y})^2 dy \end{aligned} \tag{3}$$

In other words,

$$I_{MMSE}(D,0) = I_C(D) = I_{ML}(D) \tag{4}$$

Where,

$$\left.\begin{aligned} I_{ML}(D) &= \arg\min_{y} \; p(D \mid y) \\ p(D \mid y) &= \frac{1}{\sqrt{2\pi\varepsilon^2}} e^{-\frac{1}{2\varepsilon^2}(D - E\{f(z)|y\})^2} \end{aligned}\right\} \tag{5}$$

D is the signal that is produced.MMSE is thus used for inverse transformation of the signal that is stabilized using anscombe transformation.

IV. EXPERIMENTAL RESULTS

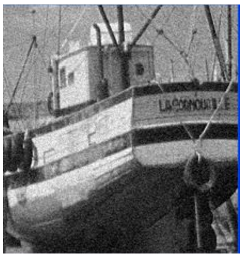

Fig 1. Original noised image

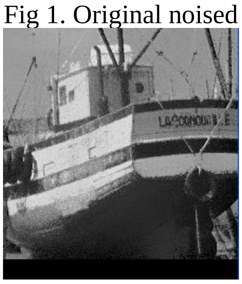

Fig 2.Filtered image using local bilateral filter

Fig 3.filtered image using Gauss filter

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Fig 4.filtered image using non local bilateral filter

Fig 5.Denoising through LEEFLIT Technique

Fig 6.Denoising through FFT Technique

V. COMPARISON RESULTS

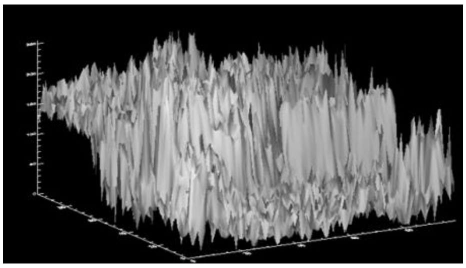

Fig 7.Original image

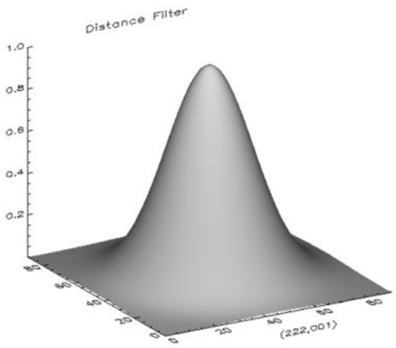

Fig 8.Distance filter

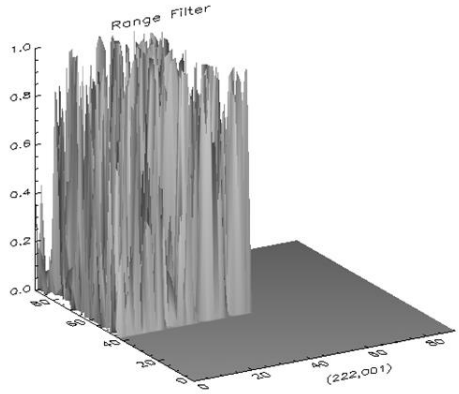

Fig 9.Range filter

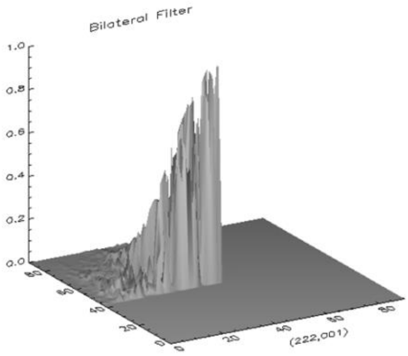

Fig 10.Bilateral filter

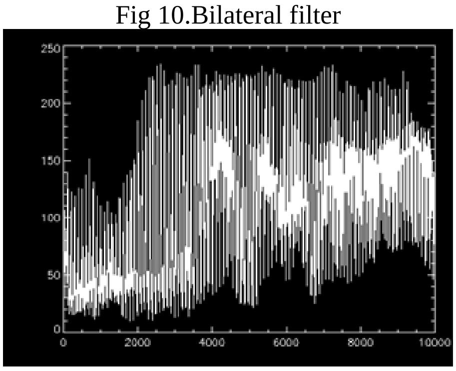

Fig 11.Fast Fourier Transform

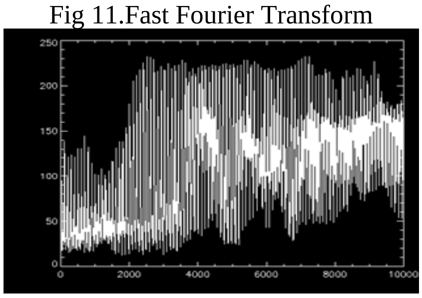

Fig 12. Leefilt filter

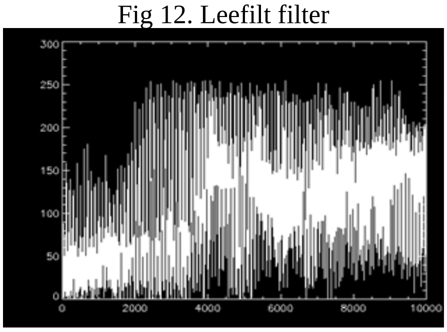

Fig 13. PCA analysis

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VI. CONCLUSION

In this paper we contemplated only imaging, but it is worth noting that the same procedure can be applied to data of any dimension, including 1-D signals and volumetric data.

Let us also remark that even though our focus is on the Anscombe transformation, there exists a variety of other variance –stabilizing transformations for Poisson data, such as the Freeman-Turkey transformation, or more optimized ones discussed in. However, the emphasis of this paper is on the improvement gained through applying a suitable inverse, rather than on the improvement gained through optimized variance stabilization. We chose to use the Anscombe transformation because it is in wide use, but the proposed method is in no way limited to this particular transformation.

Finally, we wish to note that the concept of optimal inverse transformations is of course not restricted to the Poisson distribution it can be extended to Gaussian distribution also.

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