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A Survey on Various Image Denoising & Filtering Techniques

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Abstract—*In many of the digital image processing applications, examined image is modeled to be damaged by different types of noise that consequence in a noisy description. Hence image denoising is an important problem that aims to find an approximation description from noisy image that is as close to the original image as possible. Image denoising imposes a compromise between noise reduction and preserving significant image details. To achieve a good performance in this respect, a denoising algorithm has to adapt to image discontinuities. The wavelet representation naturally facilitates the construction of such spatially adaptive algorithms. It compresses the essential information in a signal into relatively few; large coefficients which represent image details at different resolution scales. To reduces heavily processing time for decomposition of image keeping or overcoming the quality of reconstructed images.*

Keywords:—*Gabor Filter, Denoising, wavelet transform, DWT.*

1. INTRODUCTION

Denoising of signals and images is a fundamental task in signal processing. Early approaches, such as Gaussian Gabor filters and anisotropic diffusion [1], denoise the value of a signal $y(x_1)$ at a point x_1 based only on the observed values $y(x_2)$ at neighboring points x_2 spatially close to x_1. To overcome the obvious shortcomings of this locality property, many authors proposed various global and multiscale denoising approaches. Among others, we mention minimization of global energy functional such as the total-variation functional and Fourier and wavelet denoising methods [2]. Although quite sophisticated, these methods typically do not take into account an important feature of many signals and images, that of repetitive behavior, e.g., the fact that small patterns of the original noise-free signal may appear a large number of times at different spatial locations. For one-dimensional (1-D) signals these properties holds for every periodic or nearly periodic function (such as repetitive neuronal spikes, heart beats, etc.) and for many telegraph type processes. Similarly, identical patches typically appear at many different and possibly spatially distant locations in two-dimensional (2-D) images. The fact that the same noise-free pattern appears multiple instances can obviously be utilized for improved denoising.

Rather than averaging the value of a noisy signal at a point x based only on its few neighbor values, one can identify other locations in the signal where a similar pattern appears and average all of these instances. This observation naturally leads to the development of various nonlocal denoising methods [3, 4]. The characteristics of the Gabor wavelets, especially for frequency and orientation representations, are similar to those of the human visual system, and they have been found to be appropriate for texture representation and discrimination. Yi-Chun Lee and Chin-Hsing Chen [5] have proposed feature extraction for face recognition based on Gabor filters and two-dimensional locality preserving projections.

Nevertheless Gabor functions present some important drawbacks. First, it is not possible to build a complete orthogonal basis of Gabor functions, therefore non-orthogonal bases have to be employed. Non orthogonality implies that exact reconstruction using the same filters for analysis and synthesis will not be possible unless an over complete basis is considered. Secondly, Gabors are bandpass filters; they are consequently inadequate for covering the lowest and highest frequencies. Thirdly, it is particularly difficult to cover up the mid frequencies with sufficient uniformity. Gabor multi resolutions have been successfully used for image analysis and applications where exact reconstruction is not required, such as texture analysis

2. CURVELETS BACKGROUND

The construction of efficient linear expansions for two-dimensional functions which are smooth away from discontinuities across smooth curves. Such functions resemble natural images where discontinuities are generated by edges – referred to the points in the image where there is a sharp contrast in the intensity, whereas edges are often gathered along smooth contours which are created by typically smooth boundaries of physical objects. Efficiency of a linear expansion means that the coefficients for functions belonging to the class of importance are sparse, and consequently it implies well-organized illustrations for such functions using a non-linear approximation scheme.

Over the last decade, wavelets have had a growing impact on signal processing, mainly due to their good NLA performance for piecewise smooth functions in one dimension (1-D). Unfortunately, this is not the case in two dimensions (2-D). In essence, wavelets are good at catching point or zero-dimensional discontinuities, but as already mentioned, two-dimensional piecewise smooth functions resembling images have one-dimensional discontinuities. Without needing to ask, wavelets in 2-D acquired by a tensor-product of 1-D wavelets will be good at isolating the discontinuity at an edge point, but will not see the smoothness alongside the contour. This indicates that more controlling demonstrations are needed in higher dimensions.

This fact has a direct impact on the performance of wavelets in many applications. As an example, for the image denoising difficulty, modern methods are supported on thresholding of wavelet coefficients [6]. While being simple, these methods work very efficiently, for the most part due to its assets of the wavelet transform that most image information is contained in a small number of significant coefficients – around the locations of singularities or image edges. However, since wavelets fail to represent efficiently singularities along lines or curves, wavelet-based techniques fail to explore the geometrical structure that is typical in smooth edges of images. Therefore, new denoising schemes which are based on true two-dimensional transforms are expected to improve the performance over the current wavelet-based methods.

Recently, Candes and Donoho [7] pioneered a new system of demonstration, given named curvelet, that was exposed to accomplish optimal approximation behavior in a certain sense for 2-D piecewise smooth functions in R2 where the discontinuity curve is a C2 function. More specifically, an M-term non-linear approximation for such piecewise smooth functions using curvelets has L2 square error decaying like O(M−2), and this is the best rate that can be achieved by a large class of approximation processes. An attractive property of the curvelet system is that such correct approximation behavior is simply obtained via thresholding a fixed transform.

Back to the image denoising problem, there are other approaches that explore the geometrical reliability of circumferences, for illustration by chaining neighboring wavelet coefficients and then thresholding them over these contours [8]. However, the curvelet transform come within reach of, with its incorporated geometrical arrangement; provide a more direct way by simply thresholding significant curvelet coefficients in denoising images with smooth edges. The original construction of the curvelet transform [7] is based on windowing the subband images into blocks and applying the ridgelet transform on these blocks. We will show that this approach poses several problems when one tries to implement the curvelet transform for discrete images and uses it in applications. Furthermore, as the curvelet transform was originally defined in the frequency domain, it is not understandable how curvelets are illustration in the spatial domain.

In frequency domain, such ridgelet function is essentially localized in the corona $|\omega| \in [2^s, 2^{s+1}]$ and around the angle θ. The ridgelet transform to provide a sparse representation for smooth objects with straight edges. To sum up, the curvelet decomposition composes of the following steps [9]:

- Subband breakdown of the object into a progression of subbands.
- Windowing each subband into blocks of suitable size, depending on its inside frequency.
- Be appropriating the ridgelet transform on these blocks.

The motivation behind the curvelet transform is that by smooth windowing, segments of smooth curves would look straight in subimages; hence they can be well captured by a local ridgelet transform. Subband disintegration is used to maintain the number of ridgelets at multiple scales under control by the fact that ridgelets of a given scale live in a assured subband. The window's dimension and subband frequency are coordinated such that curvelets have support obeying the key anisotropy scaling relation for curves [9]:

$$\text{Width} \propto \text{length}^2$$

Curvelets and Filter Banks: The original approach for curvelet decomposition [7] poses several problems in practical applications. First, since it is a block-based transform, either the approximated images have blocking effects or one has to use overlapping windows and thus increase the redundancy. Secondly, the use of ridgelet transform, which is distinct on polar bring together, makes the accomplishment of the curvelet transform for discrete images on rectangular coordinates very challenging. In [10], different interpolation approaches were proposed to solve the polar versus rectangular coordinate transform difficulty, all necessitate over complete classifications. As a result, the description of the discrete curvelet transforms. For example has a redundancy factor equal to 16J +1where J is the number of multiscale levels. This results in the fact that curvelets are very limited in certain applications such as compression.

To overcome the problem of block-based approach, one could use a filter bank approach instead, in very much the same way as the lapped transforms. The relation between the two approaches is depicted in Figure 1. The filter bank approach as in the lapped transform can solve the blocking effect while being critically sampled. The grouping of wavelet coefficients argument in the last section suggests that we can have a curvelet like representation and thus achieve the optimal approximation rate by first be appropriating a multiscale decomposition and applying a local Radon transform to gather the basic functions in the same scale into linear structures. The local Radon decomposition can be obtained by a directional filter bank is depicted in Figure 2. That is, we first use a wavelet-like decomposition for edge or points detection, and then a local directional bases for contour segments detection. Therefore, we can achieve a curvelet like decomposition by a double filter bank in which a multi scale decomposition is used to capture the point discontinuities i.e. edge detection followed by a directional decomposition to link point discontinuities into linear structures. In this approach, the curve scaling relation is ensured by a suitable coordination between the scale and the support of the directional beginning which in rotate is relationship to the number of directions.

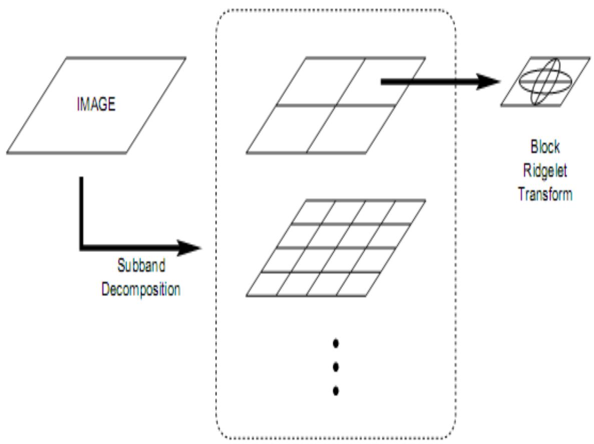

Figure 1: Curvelet decomposition by block-based approach: block ridgelet transforms are applied to subband images.

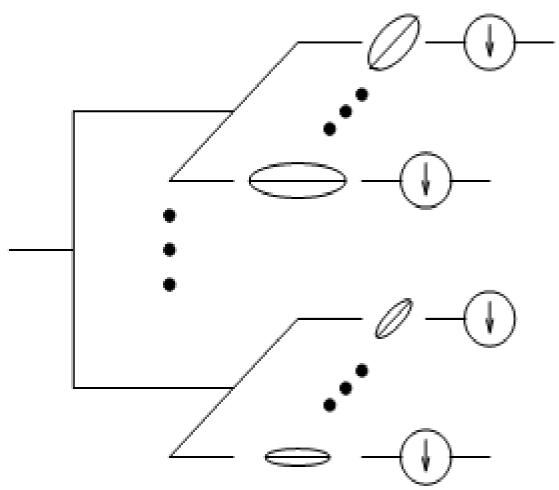

Figure 2: Curvelet decomposition image is decomposed by a double filter bank structure.

3. WAVELET-DOMAIN FILTERS

Wavelet domain filters essentially employs Wavelet Transform (WT) and for this reason are given named so. Figure 3 shows the block representation of a wavelet-domain filter. Here, the filtering operation is performed in the wavelet-domain. A brief introduction to wavelet transform is presented here.

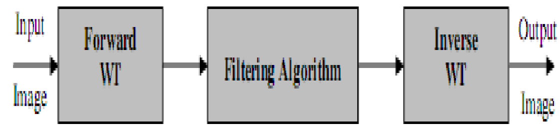

Figure 3: A Wavelet Domain Filter

Wavelet transform due to its localization property has become an indispensable signal and image processing tool for a variety of applications, including compression and denoising [11-12]. A wavelet is a mathematical function used to decompose a given function or continuous-time signal into different frequency components and study each component with a resolution that matches its scale. A wavelet transform is the representation of a utility by wavelets. The wavelets are scaled and interpreted copies known as daughter wavelets of a finite length or fast decaying oscillating waveform known as mother wavelet. Wavelet transforms are confidential into continuous wavelet transform (CWT) and discrete wavelet transforms (DWT). The continuous wavelet transform (CWT) [6] has received significant attention for its ability to perform a time-scale analysis of signals. On the other hand, the discrete wavelet transform (DWT) is an implementation of the wavelet transform using a discrete set of wavelet scales and translations obeying some definite rules. In other words, this transform decomposes the signals into mutually orthogonal set of wavelets. Such as the Haar, Daubechies, Symlets and Coiflets are compactly supported orthogonal wavelets. There are several ways of implementation of DWT algorithm.

DWT-Domain Filters: Recently, a lot of methods have been reported that perform denoising in DWT-domain [11], [13]. The transform coefficients within the subbands of a DWT can be locally modeled as independent identically distributed random variables with generalized Gaussian distribution. A number of the denoising algorithms execute thresholding of the wavelet coefficients, which have been affected by additive white Gaussian noise by maintaining only great coefficients and setting the rest to zero. These methods are popularly known as shrinkage methods. However, their performance is not quite effective as they are not spatially adaptive. A number of other techniques estimate the denoised coefficients by an (MMSE) Minimum Mean Square Error estimator in expressions of the noised coefficients and the variances of signal and noise. The signal variance is in the neighborhood approximation by a ML Maximum Likelihood estimator in small areas for every subband where variance is take for granted almost invariable. These techniques current efficient consequences but their spatial adaptively is not well ensembles near object edges where the variance field is not efficiently wide-ranging.

4. GABOR FILTERS

Gabor derived a function [14] for which the product $\Delta t \Delta f$ assumes the smallest possible value. The signal which occupies the minimum area, $\Delta t \Delta f = 1/4\pi$, is the modulation product of the harmonic oscillation of any frequency with pulse of the form of a probability function e.g., Gaussian envelope.

$\psi(t) = g(t)s(t)$ ....(i)

$$\psi(t) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(t-t_0)^2}{2\sigma^2}} e^{j2\pi f_0 t+\phi} \quad \text{……….(ii)}$$

where σ is the sharpness of the Gaussian, t0 denotes the centroid of the Gaussian, f_0 is the frequency of the harmonic oscillations, and φ denotes the phase shift of the oscillation. g (t), the Gaussian shaped function, is also known as envelope and s(t), the complex sinusoidal function, is also known as carrier. The function has a Fourier function of analytical form:

$$\Psi(f) = e^{-2\pi^2\sigma^2(f-f_0)^2} e^{-j2\pi t_0(f-f_0)+\phi} \quad \text{…(iii)}$$

It is easy to show from equation 2.13 and 2.14 that $\mu t = t_0$, $\mu f = f_0$, $\Delta t = \sigma / \surd\ 2$, $\Delta f = 1/2 \surd\ 2\pi\sigma$ and $\Delta t \Delta f = 1/4\pi$. Gabor functions may form a development space, where the individual benefit is a demonstration by optimally localized time-frequency kernels. A signal can be represented as a sum of finite number of Gabor elementary functions multiplied with specific expansion coefficients.

Gabor filters in 2D: Similarly, 2D normalized formulation of a Gabor filter has an analytical form:

$$\psi(x, y) = \frac{1}{2\pi\sigma_x\sigma_y} e^{-\left(\frac{x'^2}{2\sigma_x^2} + \frac{y'^2}{2\sigma_y^2}\right)} e^{j2\pi(f_x x' + f_y y')} \quad \text{(iv)}$$

where, x’ = x cos θ + y sin θ, y’ = −x sin θ + y cos θ, (f_x, f_y) is the frequency of the filter, σx and σy controls the spatial width of the filter, θ is the orientation of the filter, and j is $\surd -1$. To extract local frequencies, an image is convolved with a bank Gabor filter. If an image has local frequencies almost same as that of a Gabor filter, at central locations, it responds higher at all these pixels. The band-pass nature of the filter is clear by Fourier representation of a Gabor filter Convolution in spatial domain is multiplication in frequency domain.

5. LITERATURE SURVEY

Dabov et al. [15] proposed a novel image denoising strategy based on an enhancement sparse representation in transform-domain. The enhancement of sparsity is achieved by grouping similar 2-D image fragments e.g., blocks into 3-D data arrays which is called as groups. Collaborative filtering is a special procedure developed to deal with these 3-D groups. The filter is realized with three successive steps: 3-D transformation of a collection reduction of the transform range, and inverse 3-D transformation.

A spatial adaptive denoising method is developed by M. Mignotte [16] which is based on an averaging process performed on a set of Markov Chain Monte-Carlo simulations of region partition maps constrained to be spatially piecewise uniform i.e., constant in the grey level value sense for each estimated constant-value areas. For the evaluation of these area separation maps, the unsupervised

Markovian framework is adopted in which parameters are automatically estimated in least square sense.

Portilla et. al [17] build up a new method for removing noise from digital images based on a statistical model of the coefficients of an over-complete multiscale oriented basis. Neighborhoods of coefficients at adjacent positions and scales are modeled as a product of two independent random variables: a Gaussian vector and a hidden positive scalar mulitiplier. The latter modulates the local variance of the coefficients in the area, and is thus intelligent to explanation for the empirically examined correlation connecting the coefficient's amplitudes. Under this model, the Baysian least squares estimate of each coefficient reduces to a weighted average of the local linear estimates over all possible values of the hidden multiplier variable.

Ning [18] proposed a very efficient algorithm for image denoising based on wavelets and multifractals for singularity detection. By modeling the intensity surface of a noisy image as statistically self-similar multifractal process and taking advantage of the multiresolution analysis with wavelet transform to exploit the local statistical self-similarity at different scales, the point-wise singularity power value distinguishing the local singularity at each extent was computed. By thresholding the singularity strength, wavelet coefficients at each extent were classified into two categories: the edge-related and regular wavelet coefficients and the irregular wavelet coefficients. The irregular wavelet coefficients were denoised using an approximate minimum mean-squared error (MMSE) evaluation technique, at the same time as the edge-relayed and usual wavelet coefficients were smoothed using the fuzzy weighted mean (FWM) filter preserving the edges and details when reducing noise.

The framelet is an improvement upon the critically sampled DWT with important additional properties: (1) It employs one scaling function and two distinct wavelets, which are designed to be offset from one an additional by one half, (2) The double-density DWT is over-complete by a factor of two, and (3) It is nearly shift-invariant. In two dimensions, this transform outperforms the standard DWT in expressions of denoising; on the other hand, there is opportunity for improvement because not all of the wavelets are directional. Specifically, although the double-density DWT utilizes more wavelets, some lack a principal spatial orientation, which checks them from being able to separate those directions.

This paper describes new wavelet tight frames based on iterated oversampled FIR filter banks, first introduced in [19]. Selesnick et al [19] introduce the double-density wavelet transform (DDWT) as the tight-frame equivalent of Daubechie's orthonormal wavelet transform; the wavelet filters are of minimal length and satisfy certain important polynomial properties in an oversampled structure. For the reason that the DDWT, at each balance has double as many wavelets as the DWT, it achieves lower shift sensitivity than the DWT. New fast computation algorithms for computing discrete framelet transform have been described in this paper in a simple and easy to verify procedure based on iterated FIR filter bank that simplify computation complexity by using simple operations like matrix multiplication and addition.

Here author has [20] propose new approach point of reference estimation based on Gabor filters, as an alternative of the predictable approach. As the usual direction estimation is launched on the minimization of high-frequency coefficients, it is efficient for uncorrupted images but does not effort fine within corrupted images. In actual fact, the local image features may be disturbed by the noise. Then the way explained by the minimization may not exactly keep up a correspondence to the authentic orientation additionally, the noise cannot be eradicated efficiently in view of the fact that the noise energy for the most part high frequency is dense into the low-pass subband also. The schoolwork of a directional lifting transform for wavelet frames. A non subsampled lifting arrangement is developed to sustain the translation invariance as it is a significant belonging in image denoising. Then, the directionality of the lifting-based tight frame is unambiguously talk about, go after by a specific translation invariant directional framelet transform (TIDFT). The TIDFT has two framelets ψ1, ψ2 with become extinction moments of arrange two and one correspondingly, which are able to detect singularities in a given bearing set. It provides an efficient and sparse representation for images surrounding rich textures along with properties of fast accomplishment and just the thing reconstruction. So the investigational consequences give you an idea about that the TIDFT do better than some other frame-based denoising process, such as contourlet and shearlet, and is viable to the modern denoising move towards.

6. LITERATURE SURVEY

While most of the existing methods for incorporating with translation invariance, followed by a specific translation invariant directional framelet transform, and shall take advantage of the denoising capability of are designed specifically for a given type of noise, so various model appears to be the first adaptable model for handling with various mixed noises and unknown type of noises. This characteristic is mainly significant for solving real life denoising problems, in view of the fact that under various constraints images are always humiliated with mixed noise and it is unfeasible to decide what type of noise is engaged. The main difficulty behind the noise removal and denoising for real images is that there is no prior knowledge of the noise, denoising and its statistical distribution, which itself is the consequence of a mixture of different noises. Hence, models based on a specific type of noise distribution are hard to be effective. In view of the fact that design any system does not assume any prior statistical distribution of the noise, it has the potential to perform well in real image denoising.

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The preferred spelling of the word "acknowledgment" in America is without an "e" after the "g". Avoid the stilted expression, "One of us (R. B. G.) thanks" Instead, try "R. B. G. thanks". Put applicable sponsor acknowledgments here; DO NOT place them on the first page of your paper or as a footnote.

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