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Image Enhancement using Ridgelets

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ABSTRACT: One goal in image restoration is to remove the noise from the image in such a way that the original image is discernible. One well-travelled approach is to smoothe the image. The simplest version is to replace each pixel it by the average of the neighbouring pixel values. If we do this a few times we get the image in the middle above, if we do it many times, we get image on the right. On the plus side much of the spotty noise has been muted out. On the downside the sharp boundaries that make up the letters have been smeared due to the averaging. In this paper we present a new affine invariant image transform, based on ridgelets. The new method has some similarities with the previously proposed Multiscale wavelet transforms.

KEYWORDS: Time-Frequency averaging, Fourier transform, Wavelets, Continuous wavelet transforms, Ridgelets.

I. INTRODUCTION

Often in computer vision applications we need to recognize objects or scenes viewed from various directions. Although this is a natural process for humans it has proven to be a difficult problem in computer vision. A common solution for this task is a combination of image segmentation, feature extraction, and recognition. In the segmentation step we try to extract a set of patches in a way that is insensitive to possible pose changes. For doing this there exists a wide range of possible approaches, going from simple thresholding to more sophisticated methods like mean-shift segmentation [1], similarity-measure-segmentation [2], and affine covariant area detectors [3], [4]. However, the optimal choice of the method depends heavily on the specific application.

In the case of successful segmentation we still have to deal with the geometric distortion induced by the view angle change. These distortions are usually well modelled by an affine transformation, and hence it is enough to design feature extraction techniques which eliminate this effect. The related methods may be divided into two main categories. The approaches in the first category use normalization to eliminate the affine changes and only then apply some feature extraction to the normalized patches. An example of such technique could be detection of ellipses using the Harris affine detector [3], which normalizes the ellipses to circles and then applies for instance the SIFT [5] operator to them.

The image processing scientific field normally wavelet transforms used for image denoising, image compression, signal processing, pattern recognition, many image applications and computer graphics. Coifman and Donoho pointed out this algorithm exhibits visual artifacts: Gibbs phenomena in the neighbourhood of discontinuous. Consequently they propose in a translation invariant denoising scheme to suppress such artifacts by averaging over the denoised signals of all circular shifts. Bui and chen [2] extended this TI scheme to the multiwavelet case and they found that TI multiwavelet denoising gave better results than TI single wavelet denoising.

Paper is organized as follows. Section II gives information regarding related works. Section III describes image enhancement using continuous ridgelets. The flow represents the step of the algorithm. Experimental results that is given in Section IV showing noisy images and resultant images after applying ridgelets. Finally, Section V presents conclusion.

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II. RELATED WORKS

Many image processing tasks take advantage of sparse representations of image data where most information is packed into a small number of samples. Typically, these representations are achieved via invertible and non-redundant transforms. Currently, the most popular choices for this purpose are the wavelet transform [8], [9], [10] and the discrete cosine transform [11]. The success of wavelets is mainly due to the good performance for piecewise smooth functions in one dimension. Unfortunately, such is not the case in two dimensions. In essence, wavelets are good at catching zero-dimensional or point singularities, but two-dimensional piecewise smooth signals resembling images have one-dimensional singularities. That is, smooth regions are separated by edges, and while edges are discontinuous across, they are typically smooth curves. Intuitively, wavelets in two dimensions are obtained by a tensor-product of one dimensional wavelets and they are thus good at isolating the discontinuity across an edge, but will not see the smoothness along the edge. To overcome the weakness of wavelets in higher dimensions, Candès and Donoho [12], [13] recently pioneered a new.

In this paper, we propose a continuous ridgelet transform that achieves both invertibility and non-redundancy. In fact, our construction leads to a large family of orthonormal and directional bases for digital images, including adaptive schemes. As a result, the inverse transform is numerically stable and uses the same algorithm as the forward transform. Because a basic building block in our construction is the finite Radon transform [14], which has a wrap-around (or aliased line) effect, our ridgelet transform is not geometrically faithful. The properties of the new transform are demonstrated and studied in several applications. As an illustration, consider the image denoising problem where there exist other approaches that explore the geometrical regularity of edges, for example by chaining adjacent wavelet coefficients and then thresholding them over those contours [15]. However, the discrete ridgelet transform approach, with its built-in linear geometrical structure, provides a more direct way by simply thresholding significant ridgelet coefficients in denoising images with straight edges.

III. CONTINUOUS RIDGELETS

Despite the fact that wavelets have had a wide impact in image processing, they fail to efficiently represent objects with highly anisotropic elements such as lines or curvilinear structures like edges. Anisotropic elements are the ones that are elongated i.e. length is much greater than width. The reason wavelets cannot efficiently represent these objects is because they are non-geometrical and do not exploit the regularity of the edge curve. Wavelets assume that most things in an image have a full shape and that they are not particularly elongated in either direction. This works in most cases, but not all of them.

The ridgelet transforms were developed as an answer to the weakness of the wavelet transforms in sparsely representing what appears to be simple building blocks in an image, namely lines, curves and edges. Ridgelets take the form of basis elements which exhibit high directional sensitivity and are highly anisotropic. These very recent geometric image representations are built upon ideas of multiscale analysis and geometry.

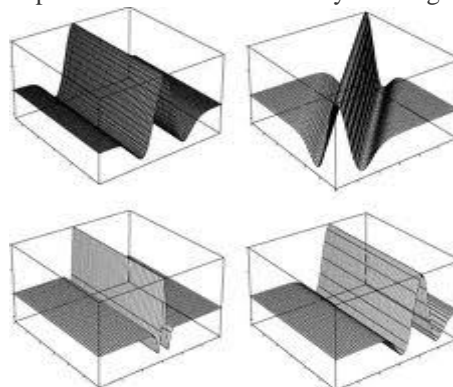


Fig 1. Ridgelet Transform (Scaling and rotation)

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Unlike wavelets, ridgelets are non-local as they are infinitely elongated in the co-direction. In the context of image processing, where one would restrict objects to reside on the unit square, ridgelet functions are roughly of unit length and have arbitrary width. This means that one would have all possible aspect ratios. This is like an addition to the features provided by a wavelet transform. We artificially *stretch* a signal to see if we can find something interesting. This is a simplified explanation of the ridgelet transform. The actual mathematical formulation is quite complex.

$$R_f(a, b, \theta) = \int \psi_{a,b,\theta}(x) f(x) dx \quad (1)$$

Where

$$\psi_{a,b,\theta}(x) = a^{\frac{1}{2}} \psi\left(\frac{x_1 \cos(\theta) + x_2 \sin(\theta) - b}{a}\right) \quad (2)$$

Algorithm

- i). Divide the image into $R \times R$ blocks with 2 vertically adjacent blocks overlapping $R = 2 / R$ pixels and two horizontally adjacent blocks overlapping $R \times R = 2$ pixels.
- ii). Each block, Apply complex ridgelets, threshold the complex ridgelet coefficients, and apply inverse complex ridgelet transform.
- iii). Proceeds the average of the denoising image pixel values at the same place.

The above algorithm call as Com Ridgelet Shrink, however the algorithm using the ordinary ridgelets Ridgelet Shrink. The computational complexity of Com Ridgelet Shrink is similar to Ridgelet Shrink by means of the scalar wavelets. The difference is that we replaced the 1D wavelet transform with the 1D dual-tree complex wavelet transform. The amount of computation for the 1D dual-tree complex wavelet is twice that of the 1D scalar wavelet transform. But, other steps of the algorithm keep the same amount of calculation. The experimental results show that Com Ridgelet Shrink outperforms Visu Shrink, Ridgelet Shrink, and wiener2 filter for all cases. In some cases, we obtain some improvement in Peak signal to noise ratio (PSNR) over Ridgelet Shrink.

IV. RESULTS

We use for famous image Lena. The below images with different noise levels are regenerated by adding Gaussian white noise to the original noise-free images. The searching, investigational results in the form of Peak signal to noise ratio. The first column of value is the PSNR of the original noisy image and other columns are the PSNR of the denoised images.

$$PSNR = -10 \log_{10} \frac{\sum_{i,j} (N(i,j) - M(i,j))^2}{n^2 255^2} \quad (3)$$

Where M is the noise-free image and N is the denoised image. The figure shows the noise free image, the image with noise added, the denoised image with Visu Shrink, the denoised image with Ridgelet Shrink, the denoised image with Com Ridgelet Shrink, and the denoised image with wiener2 for images Lena, at a partition block size of 32×32 pixels.



Fig 2. Original Image

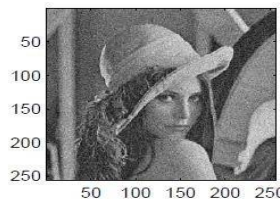


Fig 3. Noisy Image

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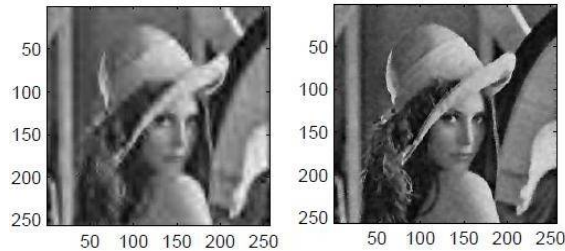


Fig 4. Wavelet Transform

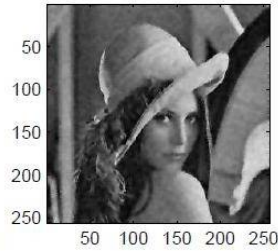


Fig 5. Resultant Image



Fig 6. Noisy Image



Fig 7. Resultant Image



Fig 8. Original Image



Fig 9. Resultant Image

V. CONCLUSION

The paper continuous ridgelet transform is obtained by execution 1D continuous wavelet on to the Ridgelet transform coefficients. The complex ridgelet transform an outstanding best for image denoising because of we uses the approximate shift invariant property of the wavelettransform. The continuous ridgelet transform provides near ideal sparsity of representation for both objects with edges and smooth objects.

This paper introduces a novel affine invariant transform. The presented approach is based on ridgelets and it further gives rise to a framework for constructing a number of other affine invariant transforms. The invariants are efficiently implemented using the Radon transform and by proper selection of the transform coefficients. We assessed the method in experiments demonstrating several distortions appearing in photographing and binarization processes, and the new method gave strong performance. In general the results illustrate that ridgelet invariants extract highly discriminative and robust information from image patches

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