Automatic Detection of Sinusitis and Analyzing the Severity with Preventive Measures using GUI MATLAB Tools

P Sasi Kiran, M. Sailaja

Abstract— Sinusitis is treated with medications or surgery for severe cases. Imaging techniques are popular in detecting sinusitis as they are less intrusive. Current imaging techniques used to detect sinusitis are the X-ray, CT scan and MRI scan. Images taken with these imaging techniques have to be interpreted by doctors manually and this gives room for inconsistency or in some cases, inaccuracy. Image segmentation is important as the results of segmentation are used for diagnosis and surgical planning. At present, manual segmentation and semi-automatic segmentations are used. Another approach is the Discrete Curvelet Transform which is a new image representation. This approach is based on the idea of representing a curve as superposition of functions of various length and width obeying the lam: width ~ length^2, this called the Curvelet Scaling Law. Due to the high ability of the Curvelet transform in representing the edges, modification of Curvelet transform coefficients to enhance the sinusitis image edges better prepares the image for the segmentation part. The software used for simulations is Image processing tools in MATLAB using GUI. Simulations are performed on images of healthy sinuses and sinuses with sinusitis.

Keywords: Curvelet Transforms, Sinusitis, GUI.

I.INTRODUCTION

We describe approximate digital implementations of two new mathematical transforms, namely, the ridgelet transform and the curvelet transform. Our implementations offer exact reconstruction, stability against perturbations, ease of implementation, and low computational complexity.A central tool is Fourier-domain computation of an approximate digital Radon transform. We introduce a very simple interpolation in Fourier space which takes Cartesian samples and yields samples on a rectopolar grid, which is a pseudo-polar sampling set based on a concentric squares geometry. Despite the crudeness of our interpolation, the visual performance is surprisingly good.

Our ridgelet transform applies to the Radon transform a special overcomplete wavelet pyramid whose wavelets have compact support in the frequency domain. Our curvelet transform uses our ridgelet transform as a component step, and implements curvelet subbands using a filter bank of à trous wavelet filters. Our philosophy throughout is that transforms should be overcomplete, rather than critically sampled. We apply these digital transforms to the denoising of some standard images embedded in white noise. In the tests reported here, simple thresholding of the curvelet coefficients is very competitive with "state of the art" techniques based on wavelets, including thresholding of decimated or undecimated wavelet transforms and also including tree-based Bayesian posterior mean methods. Moreover, the curvelet reconstructions exhibit higher perceptual quality than wavelet-based reconstructions, offering visually sharper images and, in particular, higher quality recovery of edges and of faint linear and curvilinear features.

1.1 Wavelet Image De-Noising:

Over the last decade there has been abundant interest in wavelet methods for noise removal in signals and images. In many hundreds of papers published in journals throughout the scientific and engineering disciplines, a wide range of wavelet-based tools and ideas have been proposed and studied. Initial efforts included very simple ideas like thresholding of the orthogonal wavelet coefficients of the noisy data, followed by reconstruction. Later efforts found that substantial improvements in perceptual quality could be obtained by translation invariant methods based on thresholding of an undecimated wavelet transform. More recently, "tree-based" wavelet de-noising methods were developed in the context of image de-noising, which exploit the tree structure of wavelet coefficients and the so-called parent-child correlations which are present in wavelet coefficients of images with edges. Also, many investigators have experimented with variations on the basic schemes modifications of thresholding functions, level-dependent thresholding, block thresholding, adaptive choice of threshold, Bayesian conditional expectation nonlinearities and so on. Extensive efforts by a large number of researchers have produced a body of literature which exhibits substantial progress overall, achieved by combining a sequence of incremental improvements.

1.2 A Promising New Approach:

In this project, we report initial efforts at image de-noising based on a recently-introduced family of transforms, the ridgelet and curvelet transforms, which have been proposed as alternatives to wavelet representation of image data. These transforms, to be described further below, are new enough that the underlying theory is still under development. Software for computing these new transforms is still in a formative stage, as various trades-offs and choices are still being puzzled through. Although we have completed an initial software development only, and although the time and effort we have expended in implementation, and in fine-tuning, is miniscule in Comparison to the efforts, which have been made in image

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de-noising by wavelets, we have been surprised at the degree of success already achieved. We present in this paper evidence that the new approach, in this early state of development, already performs as well as, or better than, mature wavelet image de-noising methods. Specially, we exhibit higher PSNR on standard images such as Barbara and Lena, across a range of underlying noise levels. (At our website, additional examples are provided). Our comparisons consider standard wavelet methods such as thresholding of standard undecimated wavelet transforms, thresholding of decimated wavelet transforms, and Bayesian tree-based methods. While of course the evidence provided by a few examples is *by itself* quite limited, the evidence we present is consistent with the developing theory of curvelet de-noising, which predicts that, in recovering images which are smooth away from edges, curvelet will obtain dramatically smaller asymptotic mean square error of reconstruction than wavelet methods. The images we study are small in size, so that the asymptotic theory cannot be expected to fully `kick in'; however, we do observe already, at these limited image sizes, noticeable improvements of the new methods over wavelet de-noising. By combining the experiments reported here with the theory being developed elsewhere, we conclude that the new approaches offer a high degree of promise, which may repay further development in appropriate image reconstruction problems.

II METHODOLOGY

Brief about Curvelet transform…

2.1 Curvlet Technique:

The new ridgelet and curvelet transforms were developed over several years in an attempt to break an inherent limit plaguing wavelet de-noising of images. This limit arises from the well-known and frequently depicted fact that the two-dimensional wavelet transform of images exhibits large wavelet coefficients even at fine scales, all along the important edges in the image, so that in a map of the large wavelet coefficients one sees the edges of the images repeated at scale after scale. While this effect is visually interesting, it means that many wavelet coefficients are required in order to reconstruct the edges in an image properly. With so many coefficients to estimate, denoising faces certain difficulties. There is, owing to well-known statistical principles, an imposing trade-off between parsimony and accuracy, which even in the best balancing leads to a relatively high Mean Squared Error (MSE). While this trade-off is intrinsic to wavelet methods (and also to Fourier and many other standard methods), there exist, on theoretical grounds, better de-noising schemes for recovering images which are smooth away from edges. For example, asymptotic arguments show that, in a certain continuum model of treating noisy images with formal noise parameter [illegible] , for recovering an image which is *C*2 smooth away from *C*2 edges, the ideal MSE scales like [illegible] ^(4/3) whereas the MSE acheivable by wavelet methods scales only like [illegible] . (For discussions of this white noise model). To approach this ideal MSE, one should develop new expansions which accurately represent smooth functions using only a few nonzero coefficients, and which also accurately represent edges using only a few nonzero coefficients. Then, because so few coefficients are required either for the smooth parts or the edge parts, the balance between parsimony and accuracy will be much more favorable and a lower MSE results. The ridgelet transform and curvelet transform were developed explicitly to show that this combined sparsity in representation of both smooth functions and edges is possible. The continuous ridgelet transform provides a sparse representation of both smooth functions and of perfectly straight edges. The *ridgelet transform* in two dimensions allows the representation of arbitrary bivariate functions $f(x1; x2)$ by Super positions of elements of the form $a_¡1=2\tilde{A}((x1 \cos \mu + x2 \sin \mu ¡ b)=a)$. Here $\tilde{A}$ is a wavelet, $a > 0$ is a scale parameter, μ is an orientation parameter, and b is a location scalar parameter. These so-called ridgelets are constant along ridgelines $x1 \cos \mu + x2 \sin \mu$, and along the orthogonal direction they are wavelets. Because ridgelets at fine scale a ¼ 0 are localized near lines $x1 \cos \mu+x2 \sin \mu = b$, it is possible to efficiently superpose several terms with common ridge lines (i.e. common $\mu; b$ and different scales a to efficiently approximate singularities along a line. But ridgelets also work well for representing smooth functions; in fact they represent functions in the Sobolev space $W2$ of functions with two derivatives in mean-square just as efficiently as wavelets (i.e. comparable numbers of terms for same degree of approximation). There are also various discrete ridgelet transforms { i.e. expansions into a countable discrete collection of generating elements { based on ideas of frames and orthobases. For all of these notions, one has frame/basis elements localized near lines at all locations and orientations and ranging though a variety of scales (localization widths). It has been shown that for these schemes, simple thresholding of the discrete ridgelet transform provides near optimal *N*-term approximations to smooth functions with discontinuities along lines . In short, discrete ridgelet representations solve the problem of sparse approximation to smooth objects with straight edges. In image processing, edges are typically curved rather than straight and ridgelets alone cannot yield efficient representations. However at sufficiently fine scales, a curved edge is almost straight, and so to capture curved edges, one ought to be able to deploy ridgelets in a localized manner, at sufficiently fine scales. Two approaches to localization of ridgelets are possible:

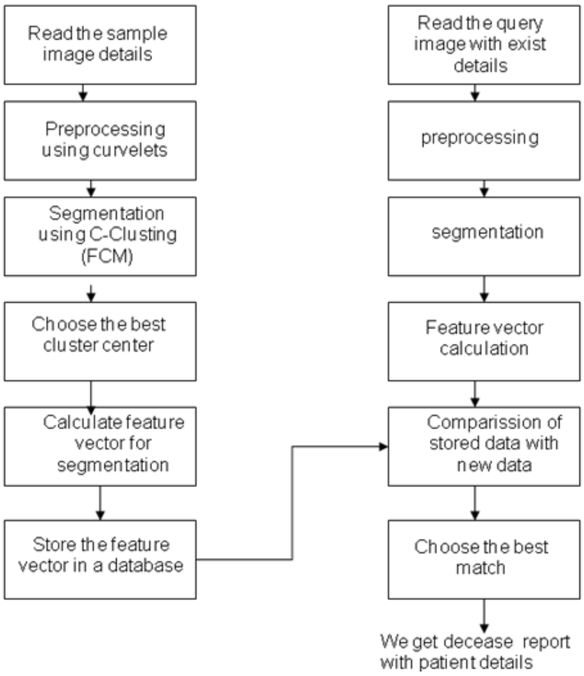
***1. Monoscale ridgelets*.** Here one thinks of the plane as partitioned into congruent squares of a given fixed sidelength and constructs a system of renormalized ridgelets Smoothly localized near each such square.

***2. Multiscale ridgelets*.** Here one thinks of the plane as subjected to an infinite series of partitions, based on dyadic scales, where each partition, like in the monoscale case, Consists of squares of the given dyadic sidelength. The corresponding dictionary of generating elements is a pyramid of windowed ridgelets, renormalized and transported to a wide range of scales and locations. Both localization approaches will play important roles in this project. Curvelets are based on multiscale ridgelets combined with a spatial bandpass filtering operation to isolate different scales. Like ridgelets, curvelets occur at all scales, locations, and orientations. However, while ridgelets all have global length and variable widths, curvelets in addition to a variable width have a variable length and so a variable anisotropy.

The length and width at fine scales are related by a scaling law *width* ¼ *length*2 and so the anisotropy increases with decreasing scale like a power law. Recent work shows that thresholding of discrete curvelet coefficients provide near-optimal *N*-term representations of otherwise smooth objects with discontinuities along *C*2 curves.

Quantitatively, the *N*-term squared approximation error by curvelet thresholding scales like *log*(*N*)3=*N*2. This approximation- theoretic result implies the following statistical result. By choosing a threshold so that one is reconstructing from the largest *N*~ ϵ ^(2/3) noisy curvelet coefficients in a noisy image at noise level ϵ , one obtains decay of the MSE almost of order *O*(ϵ ^(4/3)). In contrast, in analyzing objects with edges, wavelets give an *N*-term squared approximation error only of size *N*¡1, and wavelet thresholding gives a corresponding MSE only of size *O*(ϵ) and no better.

2.2 Algorithm



Give basic algorithm used for Curvlet..

III. PROCESSING STEPS

The Curve let Transform includes four stages:

- *Sub-band decomposition*
- *Smooth partitioning*
- *Renormalization*
- *Ridge let analysis*

1. *Sub-band Decomposition*

$$f \mapsto (P_0 f, \Delta_1 f, \Delta_2 f, \ldots)$$

- *Dividing the image into resolution layers.*
- *Each layer contains details of different frequencies:*
  - P_0 *– Low-pass filter.*
  - $\Delta_1, \Delta_2, \ldots$ *– Band-pass (high-pass) filters.*
- *The original image can be reconstructed from the sub-bands:*

$$f = P_0(P_0 f) + \sum_s \Delta_s(\Delta_s f)$$

- *Energy preservation*

$$\|f\|_2^2 = \|P_0 f\|_2^2 + \sum_s \|\Delta_s f\|_2^2$$

- *Low-pass filter* Φ_0 *deals with low frequencies near* $|\xi| \le 1$.
- *Band-pass filters* Ψ_{2s} *deals with frequencies near domain* $|\xi| \in [2^{2s}, 2^{2s+2}]$.
- *Recursive construction –* $\Psi_{2s}(x) = 2^{4s}\Psi(2^{2s}x)$.
- *The sub-band decomposition is simply applying a convolution operator:*

$$P_0 f = \Phi_0 * f \qquad \Delta_s f = \Psi_{2s} * f$$

2. *Smooth partitioning*

- *A grid of dyadic squares is defined*

$$Q_{(s,k_1,k_2)} = \left[\frac{k_1}{2^s}, \frac{k_1+1}{2^s}\right] \times \left[\frac{k_2}{2^s}, \frac{k_2+1}{2^s}\right] \in \mathbf{Q}_s$$

$\mathbf{Q}_s$ *– all the dyadic squares of the grid.*

- *Let w be a smooth windowing function with 'main' support of size* $2^{-s} \times 2^{-s}$.
- *For each square,* w_Q *is a displacement of w localized near Q.*
- *Multiplying* $\Delta_s f$ *with* w_Q ($\forall Q \in \mathbf{Q}_s$) *produces a smooth dissection of the function into 'squares'.*

$$h_Q = w_Q \cdot \Delta_s f$$

3. *Renormalization*

- *Renormalization is centering each dyadic square to the unit square* $[0,1] \times [0,1]$.
- *For each Q, the operator* T_Q *is defined as:*

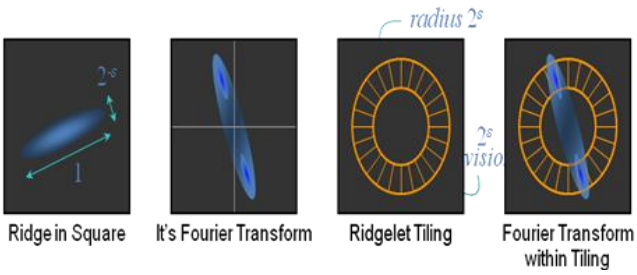
$$(T_Q f)(x_1, x_2) = 2^s f(2^s x_1 - k_1, 2^s x_2 - k_2)$$

- *Each square is renormalized:*

$$g_Q = T_Q^{-1} h_Q$$

4. *Ridge let analysis:*

Ridgelet are an orthonormal set $\{\rho_\lambda\}$ *for* $L^2(\Re^2)$. *Developed by Candès and Donoho (1998).*



- *Divides the frequency domain to dyadic coronae* $|\xi| \in [2^s, 2^{s+1}]$.
- *In the angular direction, samples the s-th corona at least* 2^s *times.*
- *In the radial direction, samples using local wavelets.*
- *The ridgelet element has a formula in the frequency domain:*

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$$\hat{\rho}_{\lambda}(\xi)=\tfrac{1}{2}|\xi|^{-\frac{1}{2}}\left(\hat{\psi}_{j,k}(|\xi|)\cdot\omega_{i,l}(\theta)+\hat{\psi}_{j,k}(-|\xi|)\cdot\omega_{i,l}(\theta+\pi)\right)$$

where,

- $\omega_{i,l}$ *are periodic wavelets for* $[-\pi, \pi)$.
- *i is the angular scale and* $l \in [0, 2^{i-1}-1]$ *is the angular location.*
- $\psi_{j,k}$ *are Meyer wavelets for* $\Re$.
- *j is the ridgelet scale and k is the ridgelet location.*

3.2 Image Segmentation:

Image segmentation is an image analysis process that aims at partitioning an image into several regions according to a homogeneity criterion. Image segmentation is a very complex task, which benefits from computer assistance, and yet no general algorithm exists. It has been a research field in computer science for more than 40 years now, and the early hope to find general algorithms that would achieve perfect segmentations independently from the type of input data has been replaced by the active development of a wide range of very specialized techniques. Most of the existing segmentation algorithms are highly specific to a certain type of data, and some research is pursued to develop generic frameworks integrating these techniques.

Segmentation can be a fully automatic process, but it achieves its best results with semi-automatic algorithms, i.e. algorithms that are guided by a human operator. This concept of semi-automatic process naturally involves an environment in which the human operator will interact with the algorithms and the data in order to produce optimal segmentations. The simplest example of the need of a human intervention during the task of segmentation results from the specificity of the existing algorithms: depending on the type of input data, the operator will have to carefully pick the best adapted algorithm, which most of the time cannot be done in an automatic way. The subjective point of view of the human is required.

Fuzzy C-Means:

The fuzzy c-means algorithm, like the k-means algorithm, the fuzzy c-means aims to minimize an objective function. The fuzzy c- mean algorithm is better than the k-mean algorithm, since in k-mean algorithm, feature vectors of the data's set can be partitioned into hard clusters, and the feature vector can exactly be a member of one cluster only. Instead, the fuzzy c-mean relax the condition, and it allows the feature vector to have multiple membership grades to multiple clusters, Suppose the data set with known clusters and a data point which is close to both clusters but also equidistant to them. Fuzzy clustering gracefully copes with such dilemmas by assigning this data point equal but partial memberships to both clusters that is the point may belong to both clusters with some degree of membership grades varies from 0 to 1.

Example:

Suppose we have taken the data in table (1). We choose k = 2 (two clusters), where k is a number of clusters, and we use both crisp clustering method and fuzzy clustering method to make 2 clusters. Instead, in the fuzzy clustering, the object belongs to both clusters with different degrees of memberships.

IV. RESULTS AND DISCUSSIONS

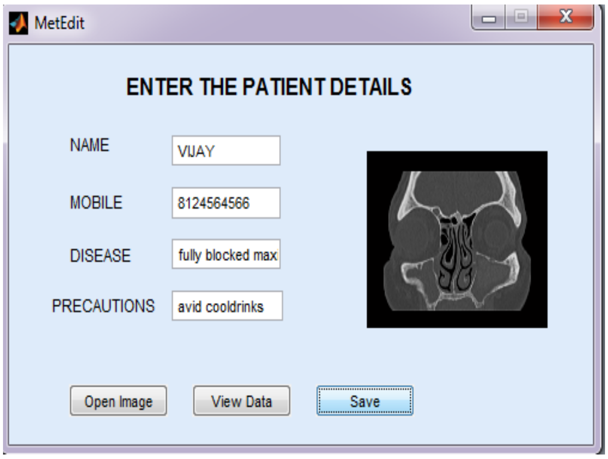

Fig : 1 Patient details and corresponding image

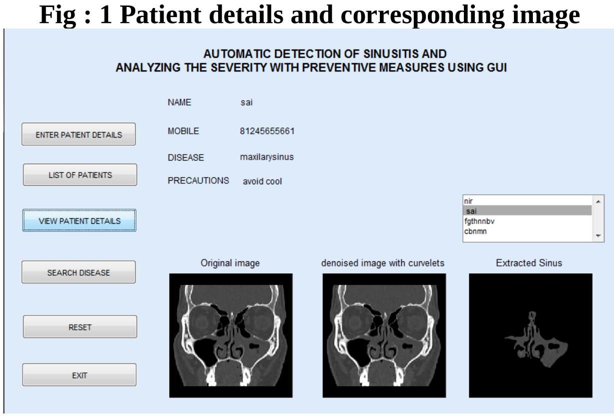

Fig : 2 Analyzing patient disease and corresponding treatment

In the figure 1 we will enter the patient details like patient name, patient phone number, disease severity and precaution for further treatment. And in the figure 2 we will analyze the patient disease and show the extracted sinus part. Like that we can implement any number of patients and we can save all the patients details.

V. CONCLUSION

In summary, a medical system for the automatic diagnosis of the primary signs of sinus has been developed by maintaining the database which addresses the severity and preventive measures. The results demonstrated with the various samples of sinus images and this algorithm proven to be well suited in complement the screening of sinusitis helping the otolaryngologist in their daily practice.

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