

Extraction of sinus using fuzzy c-means clustering using MATLAB GUI tools

I. SIDDHARTHA ¹, Y.RATNA KUMAR ²

¹(PG Scholar, Dept. of Electronics and Communication Engineering, College of Engineering(A), Andhra University, Visakhapatnam, Andhrapradesh, India)

²(Asst.Professor(C), Dept. of Electronics and Communication Engineering, College of Engineering (A), Andhra University, Visakhapatnam, Andhra Pradesh, India)

Abstract: Sinusitis with severe infections can be treated with medications or surgery. Imaging techniques is widely used in detecting sinusitis as they are considered as less intrusive. The commonly used imaging techniques are X-ray, CT scan and MRI scan. The scans obtained from these imaging techniques are to be interpreted by doctors manually where the problem of inconsistency in diagnosing the disease lies. Image segmentation can be used as aid for diagnosis. Other than manual and semi-automatic segmentation there is another approach is the Discrete Curvelet Transform which is a new representation of images. This approach is based on the idea of representing a curve as superposition of functions of length and width obeying the the Curvelet Scaling Law. The simulations are done with the help of MATLAB and GUI. The data used in the form of 30 slice CT-images of sinuses obtained from Medall laboratories, KGH, Visakhapatnam.

Keywords: Curvelet Transforms, Fuzzy C-means, GUI, Matlab, Sinusitis.

I. INTRODUCTION

This paper describes about the extraction process of the sinuses of patient data obtained from CT scans using clustering techniques. Section 1 of heading II describes the introduction, section 2 contains the methodologies, section 3 contains processing steps, section 4 contains image segmentation and section 5 contains fuzzy c-means.

II. BACKGROUND

1. Introduction

Due to the similarity and the nature of the sinus diseases and the complexity of their medical images, e.g. CT scans, which are used for the assessment of their conditions, their initial diagnosis can be a fairly complex and demanding process. It involves the use of multiple sources of information (e.g., laboratory and visual tests, CT-scans). Further, the diagnosis process requires normally the expertise of a radiologist in addition to the ENT (Ear throat and Nose) consultant.

During the diagnosis an ENT doctor has to use multiple threads of reasoning employing qualitative and quantitative measures to arrive at a diagnosis. Such decisions are harder to make when the related etiology is hard to discern or when multiple diseases are suffering. Discussions with ENT consultants and radiologists highlighted the need for an automated computer-based analysis and diagnostic tool that can be used, not only as an aid to experts, but also for use in the training of doctors and medical students.

We describe approximate digital implementations of two new mathematical transforms, namely, the ridgelet transform and the curvelet transform.

2. Methodology

2.1 Curvelet Technique:

Curvelets are a non-adaptive technique for multi-scale object representation. Being an extension of the wavelet concept, they are becoming popular in similar fields, namely in image processing and scientific computing.

Wavelets generalize the Fourier transform by using a basis that represents both location and spatial frequency. For 2D or 3D signals, directional wavelet transforms go further, by using basis functions that are also localized in orientation. A curvelet transform differs from other directional wavelet transforms in that the degree of localisation in orientation varies with scale. In particular, fine-scale basis functions are long ridges; the shape of the basis functions at scale j is 2^{-j} by $2^{j/2}$ so the fine-scale bases are skinny ridges with a precisely determined orientation.

Curvelets are an appropriate basis for representing images (or other functions) which are smooth apart from singularities along smooth curves, where the curves have bounded curvature, i.e. where objects in the image have a minimum length scale. This property holds for cartoons, geometrical diagrams, and text. As one zooms in on such images, the edges, they contain appear increasingly straight. Curvelets take advantage of this property, by defining the higher resolution curvelets to be more elongated than the lower resolution curvelets. However, natural images (photographs) do not have this property; they have detail at every scale. Therefore, for natural images, it is preferable to use some sort of directional wavelet transform whose wavelets have the same aspect ratio at every scale.

To construct a basic curvelet Φ and provide a tiling of the 2-D frequency space, two main ideas should be followed:

1. Consider polar coordinates in frequency domain
2. Construct curvelet elements being locally supported near wedges

So as 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:

- i. Monoscale ridgelets. Partitioned into congruent squares of a given fixed sidelength constructs a system of renormalized ridgelets smoothly localized near each square.
- ii. Multiscale ridgelets. 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.[6]

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 one scale related by a scaling law $\text{width} = \text{length}^2$ and so the anisotropy increases with decreasing scale like a power law.[7]

3. Processing steps

The Curve let Transform includes four stages:

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

3.1 Sub-band Decomposition

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

$$f = P_0(P_0 f) + \sum_s \Delta_s(\Delta_s f) \quad \dots \dots \dots \text{equation (1)}$$

- The sub-band decomposition is simply applying a convolution operator

3.2 Smooth partitioning

- A grid of dyadic squares is defined

- For each square, w_Q is a displacement of w localize near Q .

3.3 Renormalization

Renormalization is centering each dyadic square to the unit square.

Ridgelet analysis

Ridgelet are an orthonormal set $\{\rho_\lambda\}$ for $L^2(\mathbb{R}^2)$. Developed by Candes and Donoho (1998).

- Divides the frequency domain to dyadic coroneae
- In the angular direction, samples the s -th corona at least 2^s times.
- In the radial direction, samples using local wavelets.

4. Image segmentation

Segmentation is the name given to the generic process by which an image is subdivided into its constituent regions or objects. There are three basic properties/qualities in images which we can exploit in our attempts to segment images.

- Colour is, in certain cases, the simplest and most obvious way of discriminating between objects and background.
- Texture is a somewhat loose concept in image processing. It does not have a single definition but, nonetheless, accords reasonably well with our everyday notions of a 'rough' or 'smooth' object.
- Motion of an object in a sequence of image frames can be a powerful cue. When it takes place against a stationary background, simple frame-by-frame subtraction techniques are often sufficient to yield an accurate outline of the moving object.

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.

5. Fuzzy C-Means

Fuzzy c-means (FCM) is a data clustering technique wherein each data point belongs to a cluster to some degree that is specified by a membership grade. This technique was originally introduced by Jim Bezdek in 1981 [Bez81] as an improvement on earlier clustering methods.

Fuzzy c-means (FCM) is a data clustering technique in which a dataset is grouped into n clusters with every data point in the dataset belonging to every cluster to a certain degree. For example, a certain data point that lies close to the center of a cluster will have a high degree of belonging or membership to that cluster and another data point that lies far away from the center of a cluster will have a low degree of belonging or membership to that cluster.

Fuzzy c -means is the fuzzy version of the K-means, while the original non-fuzzy technique is called the crisp c -means or hard c -means, as the number of clusters is denoted by c instead of K . [8]

III. FIGURES AND TABLES

Figure 1 shows the algorithm of the process.

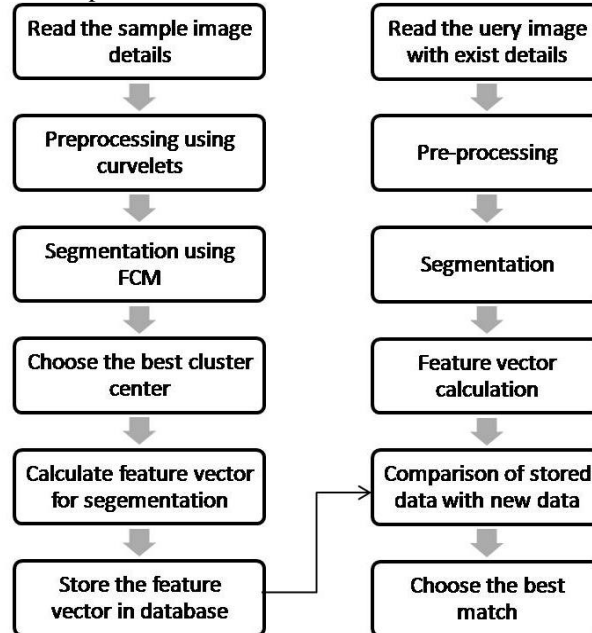



Fig1. Algorithm

Figure 2 shows a MATLAB Graphical User Interface (GUI) in which we can enter the patient details for further treatment.

ENTER THE PATIENT DETAILS

NAME	ANITHA
AGE	40
GENDER	FEMALE



OPEN IMAGE VIEW DATA SAVE

EXIT

Fig1. Patient details and corresponding image

Figure 3 shows a GUI in which we can extract the sinus part of the patient's image.

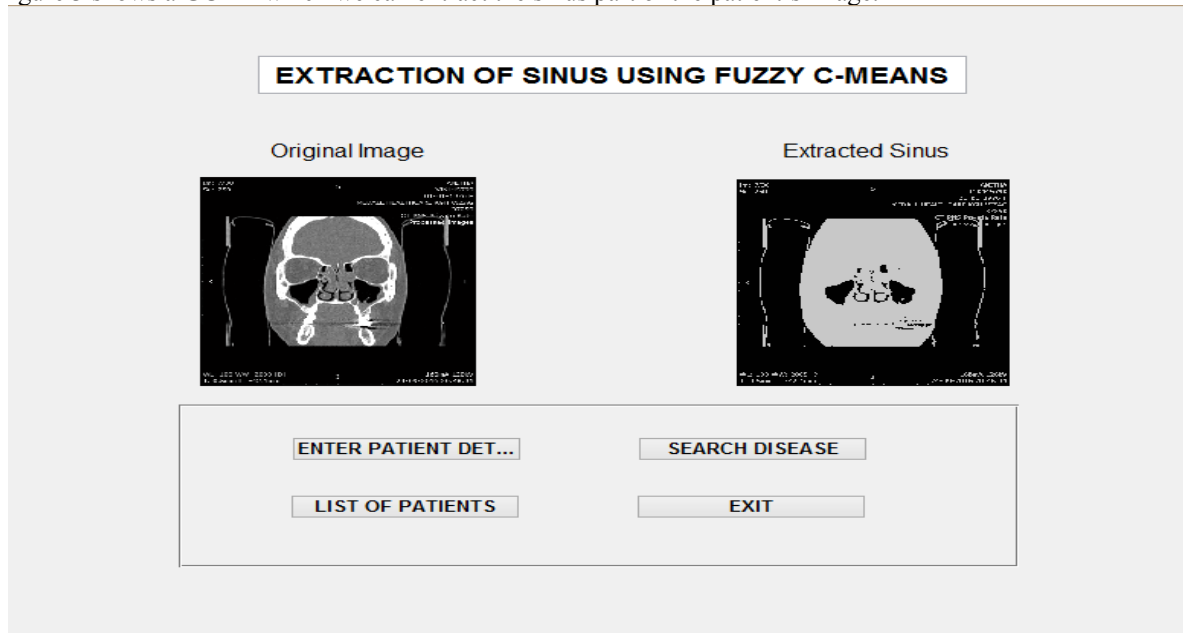


Fig3. Extracted sinus of the original patient's image

We can perform this on number of patient details and save the database for future reference.

IV. CONCLUSION

In summary, a medical system for the automatic extraction of sinus has been developed. The databases are stored for future reference. This will aid the doctors in the diagnosis of the sinuses infected with sinusitis without inconsistency. The GUI developed is user friendly and is helpful for the technicians to enter the details and retrieve them whenever needed.

REFERENCES

Journal Papers:

- [1]. Lila Iznita I., Vijanth S.A., Venkatachalam P.A., Computerized Segmentation of Sinus Images
- [2]. Z. Salah, D. Bartz, F. Dammann, E. Schwaderer, M. Maassen, W. Strasser, "A Fast and Accurate Approach for the Segmentation of the Paranasal Sinus". in: Proc. of Workshop Bildverarbeitung in der Medizin 2005, 2005, pp. 93-97.

Books:

- [3]. R. Patrick Marchand, O Thomas Holland, Graphics and GUIs with MATLAB
- [4]. J. Valente de Oliveira, W. Pedrycz, Advances in Fuzzy Clustering and its applications
- [5]. Chris Solomon, Toby Breckon, Fundamentals of digital image processing
- [6]. Information Resources Management Association, Medical Imaging: Concepts, Methodologies, Tools and Applications
- [7]. Soman K.P., Insight Into Wavelets : from Theory to Practice
- [8]. Sadaaki Miyamoto, Hidetomo Ichihashi, Katsuhiro Honda, Algorithms for Fuzzy Clustering: Methods in c-Means Clustering with Applications.