

AUTOMATED TOOL FOR THE EXTRACTION OF HEALTHY SINUS AREA

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Abstract

Sinus diagnosis has proven to be a difficult task due to the complexity of the image obtained using the computed Tomography (CT). This makes image processing and analysis difficult and time consuming. The aim of this paper is to investigate and implement a technique for the extraction of healthy maxillary and ethmoid sinuses. The proposed algorithm involves the use of neural network (self-organising map) for image processing. The self organising map (SOM) was trained using sample image which is a cut out from the CT-image of an anonymous patient. SOM learns to classify input vector according to how they are grouped. This algorithm works by first automatically reducing the input image which is usually (1012x938) pixels to (452 x 500). The next step involves reassigning all pixels in the input image with the trained SOM thereby automatically thresholding the image. Next the resulting image is inverted to make the region of interest visible against a black background and using image processing technique it crops the unwanted background and finally displays the region of interest (ROI). Data used were supplied by the John Dalton research group of the Manchester Metropolitan University. The CT scans were of anonymous patient from Trafford general hospital. All analysis was done under the Matlab environment.. The technology is based on the traditional image processing technique and Artificial Neural Network (ANNs) self organising map (SOM). The result obtained shows that the proposed algorithm is promising in the sinus extraction with the possibility to extend to the diagnosis of abnormalities. Further work would be to extend the extraction system to cover all sinuses (Maxillary, Frontal, Ethmoid, Sphenoid) and also for diagnosis of abnormalities in the sinus. In future the system would also find its usefulness in the area of training junior doctors.

Keywords: Sinus diagnosis, computed Tomography (CT) self organising map (SOM), Artificial Neural Network (ANNs)

1. Introduction

The development of an automated tool for extraction of sinus region is a challenging and yet an interesting topic in the medical image processing and artificial intelligence research area. Diagnosis of sinus conditions is a process that involves the use of laboratory and visual test, CT images and expertise of a clinician in interpreting the image. The diagnosis of sinus condition in medicine is seen as a difficult task due to the size and complexity of the image, hence the importance of selecting just the sinus region automatically for further process of diagnosis[1]. Many advances in medicine have arise over the past years due to large scale integration and of computer for storing and correlating information as technology expanded computer came into use for diagnostic medicine, surgery planning and automatic segmentation of biomedical images[2-6]. Image processing and high performance computers and advanced imaging capabilities have facilitated major progress towards the realization of forming the images. Computer

scientists from image processing background have also contributed to work done in this area. Medical Imaging such as magnetic resonance (MR) and computed tomography (CT) are used to produce accurate 3D images of different organs and tissue [7]. In this paper emphasis is based on CT-images. Previous works has reported importance of using artificial neural networks (ANNs) in enhancing diagnosis and early intervention diagnosis [8]. Literature review shows the importance using ANNs have not been exploited for diagnosis in the sinus research area. Diagnosis of disease in sinus is done using a variety of image-based information (CT scan). The proposed system combines the artificial neural network (self organising map).

The self-organising map (SOM) is a learning algorithm that was originally proposed by kohonen [9-10]. This is a neural network method that has found increasing interest in the field of medical image processing.

The rest of the paper is organised as follows section 2 presents the sinus anatomy section 3 presents CT image feature analysis section 4

presents the sinus extraction system, section 5 presents the result of the sinus extraction system and Discussion and conclusion is presented in section 6.

2. Sinus Anatomy

The Paranasal sinus system consist of eight (four pairs) air filled spaces or sinuses within the bone of the skull and face. These are divided into sub groups that are named according to which bone they lie under [1]. They include:-

- The Ethmoid Sinus; there are approximately 8-15 ethmoidal air cells which form a bony labyrinth in the upper and lateral of the nasal cavity, a condensation of the bony portions which makes up the division of the ethmoidal air cells, is called the ground lamella and divides the anterior from the posterior ethmoidal air cells.
- The Maxillary Sinus; the maxillary sinus is housed in the maxilla with roots of the upper premolars and molars projecting into its floor,

with its medial wall open and filled by the inferior turbinate, the uncinata bone above the ethmoid behind the maxillary ostia or hole draws into a slit like opening into the nasal air way and this also aerates the sinus. The uncinata bone is a thin but important bone as it makes up the medial wall of slit. The infundibulum which passes from the hiatus semi lunaris to the maxillary sinus.

- The sphenoid Sinus; the ostium of the sphenoid sinus lies in the posterior wall of the nose approximately 1cm above the area posterior choana fall into the oropharynx. Its closely related to the optic nerve and carotid artery which lie in its lateral wall.
- The frontal sinus; this is a variable three dimensional space whose boundary is influenced by its size and height of the ethmoid or agger nasi cells laterally and anteriorly and the way the uncinata process joins either the lateral wall, the middle turbinate or anterior skull bone[11]

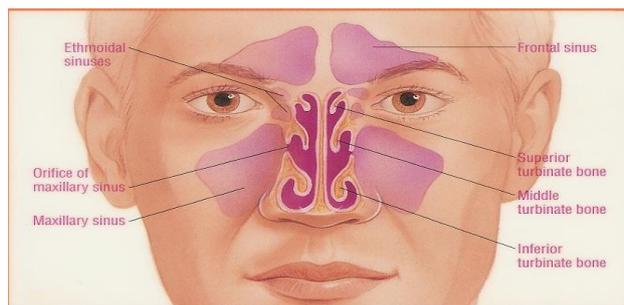


Figure 1. Sinus Anatomy (www.ghorayeb/anatomysinuses.html)

3 CT Image Feature Analysis

CT Image scan are important tool for sinus diagnosis, the figure2 below shows the sinus area been highlighted.



Figure2.highlighted sinus area (ROI)

All the sinuses cannot just be seen from just one view, the figure 3 below shows typical sinus in different angular position. The CT image used has a resolution of 1012 x 938. CT image is a grey scale

image each consist of a number of pixels with scale intensity in the range of [0-255] or if normalised range from [0-1].

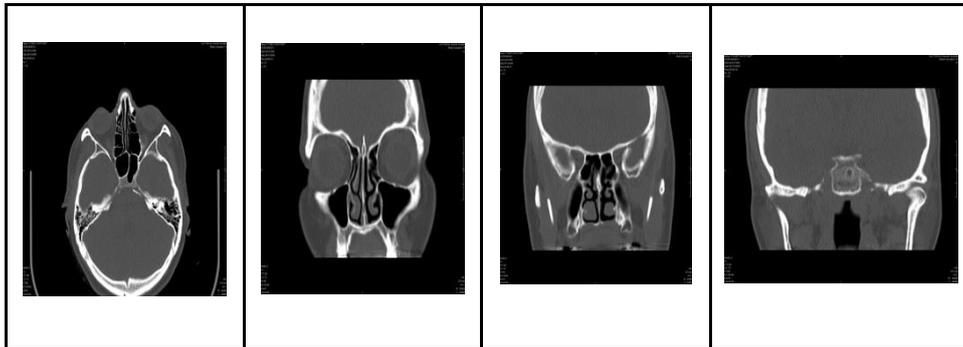


Figure3. Typical sinus in different angular position.

Multi-scale feature is one the important and noticeable feature that makes analysis of sinus CT-image tedious. Multi scale means that the image can have scale variation in shape, size and angle. Different patients have different skull bone structure hence different anatomy structure of sinuses.

4. Sinus Extraction System

This section shows how the system extracts the region of interest and what happens at every stage of the extraction process. Image

processing is an essential phase in medical imaging [12]. Most CT images generally have a blurred edge which needs to be processed. This paper focuses on the extraction of healthy sinus area (maxillary and ethmoid) from a CT-image. Due to the complexity of the image it would be computationally less expensive and faster to process just the wanted area. The technology used is based on a combination of image processing technique and artificial neural network (SOM). The figure4 shows the stages involved in the extraction process

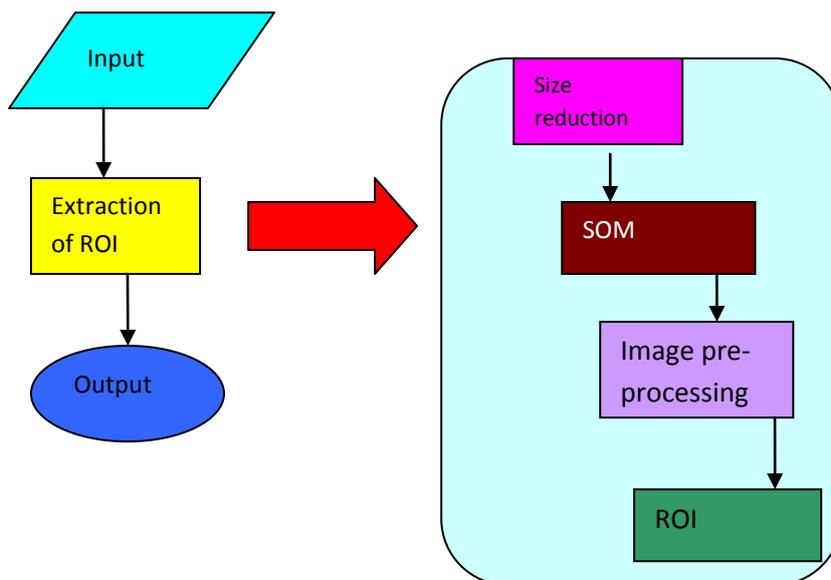


Figure 4. The stages of the sinus extraction process.

Image pre-processing is an essential phase in medical imaging [12]. CT images generally have blurred images which need to be processed. Filtering methods were applied for smoothing, sharpening and enhancing image edges. The figure below shows the original image and the filtered image.

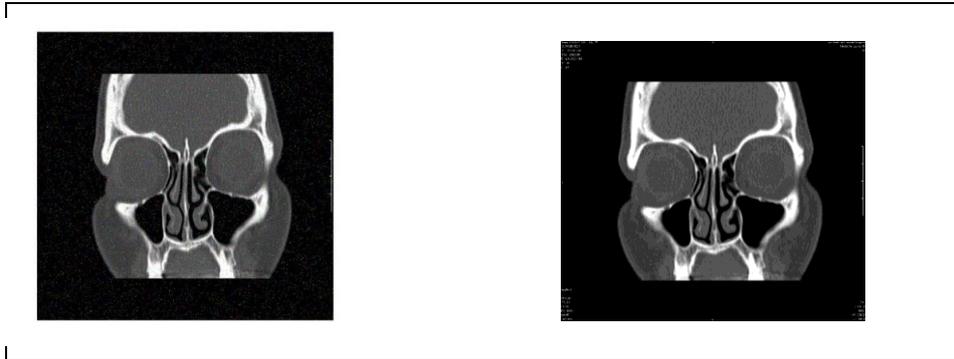


Figure 5a original image

figure 5b filtered image

At this size reduction stage, the filtered CT image with original size 1012 x 938 pixels which is too large and computationally very expensive. The idea of this section of the project is to compress the data for easy and faster computation. Hence the importance to reduce the image size keeping

relevant information. In other to achieve this, a code was written in Matlab to automatically reduce the image from 1012 x 938 to 452 x 500. The figure 6a and b shows the image before and after reduction without affecting the quality of the image.

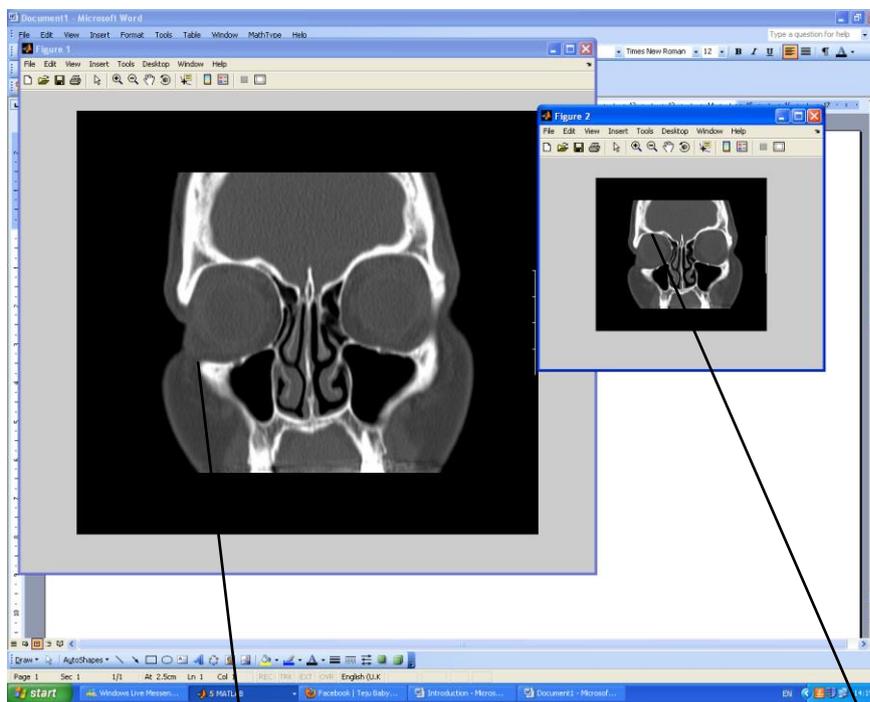


Figure 6a Original image

figure 6b Reduced image

From the histogram from the figure below it can be shown that the image quality is not affected as the histogram of images are the same.

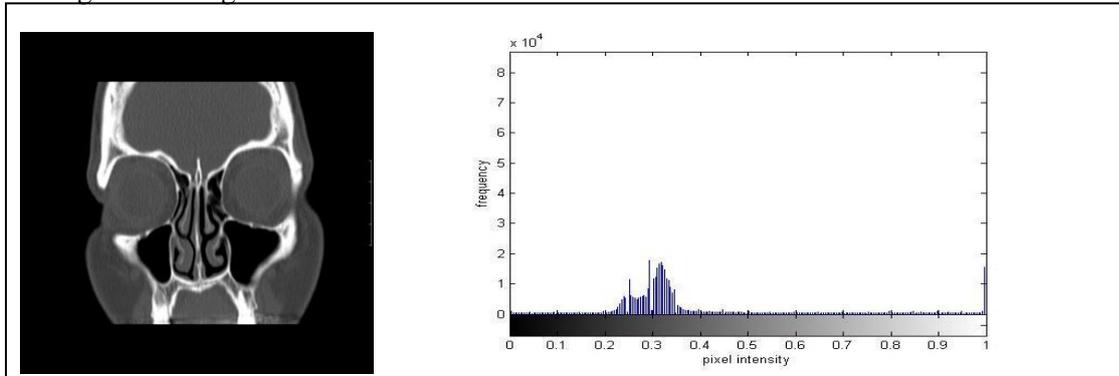


Figure 7. Shows the original image (1012 x938) and histogram

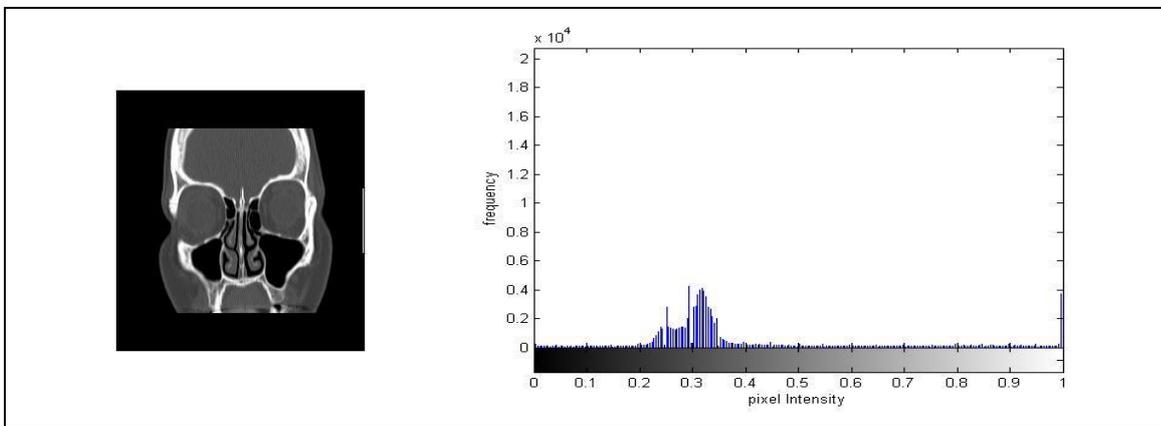


Figure 8. Shows the reduced image (452 x 500) and histogram

The next stage is the self organising map (SOM) at this stage a test image was trained for 200 epochs. This stage acts as a segmentation technique. Extraction of region of interest (ROI) is a difficult task as commonly used technique such as template matching cannot be used because of the high variation in sinus image area taken at different angle. The variation of sinus anatomy from one individual to another also makes it more difficult for template matching to work. In typical image processing application threshold is used to segment

the CT images depending on intensity values [13]. In this application the sinus extraction system segments the CT image based on the weight of the self organising map which was set to >0.2 same value in which the global threshold operates.

At this point the extraction system can now accept input image, automatically reduce the image and segments the image when it's been simulated with an input image. The figure below shows the display of the result to this point.



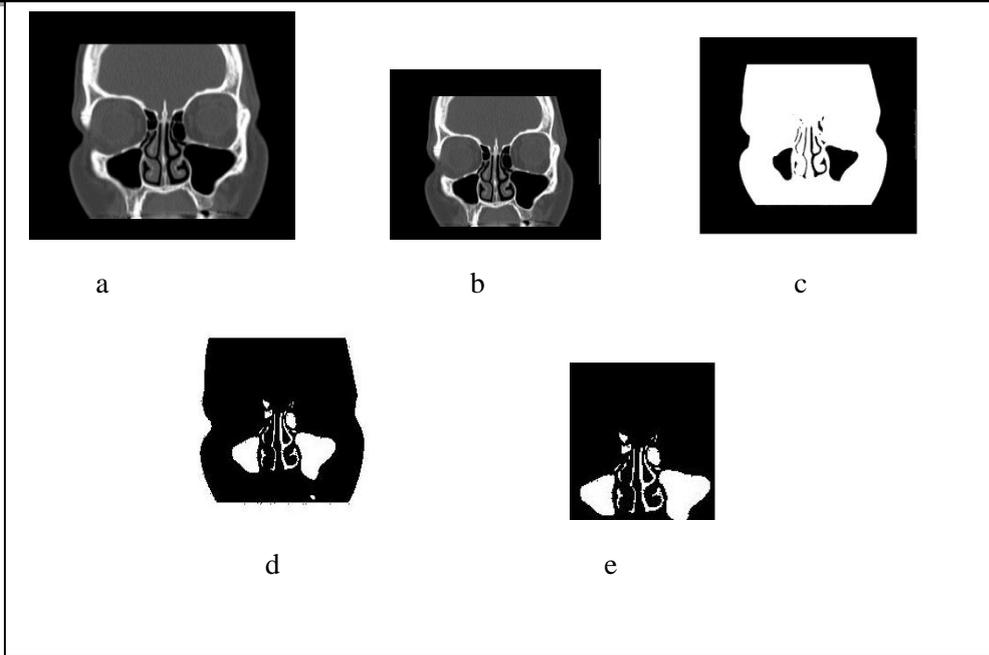


Figure 11. Graphical steps in the sinus extraction system

This algorithm was applied to numerous anonymous CT images but in the context of this thesis, the result of four of the images would be displayed. Section 5.1 shows the test result on four different images, with each step. Figure 31a shows

the original input image, b shows the reduced image and c shows the SOM result, at this point the trained network is applied to the input image and d shows the inverted image and finally e shows the extracted region of interest

5.1. Test on Images.

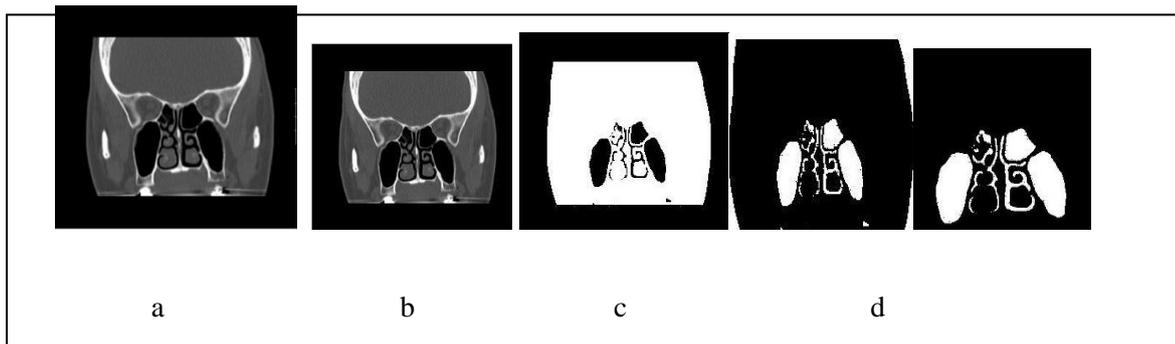


Figure 12 display of result of test image one

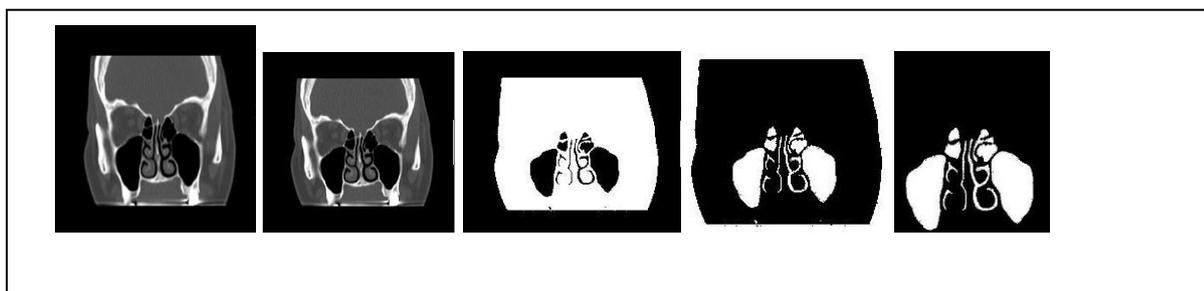


Figure 13. Display of result of test on image two

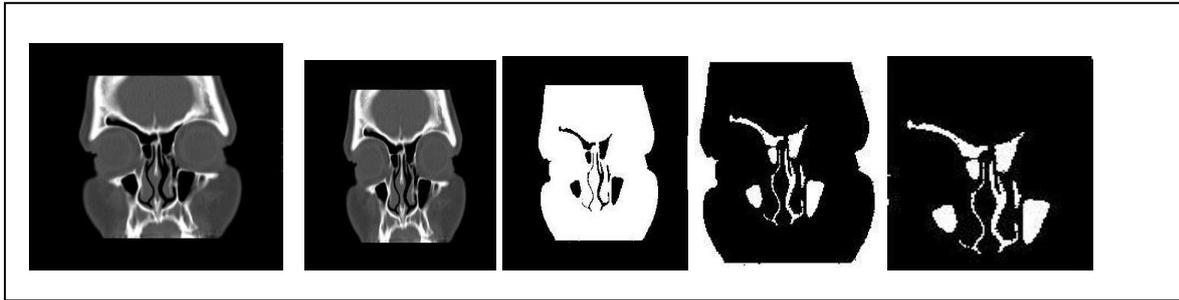


Figure 14. Display of result of test on image three.

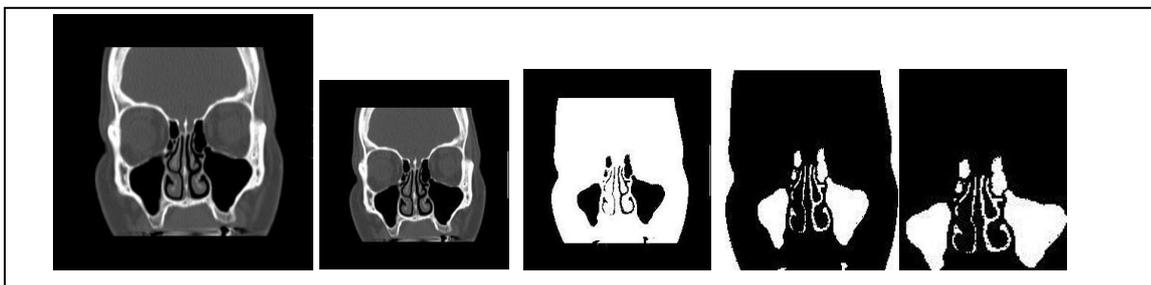


Figure 15. Display of result of test on image four

The figures 12 -15 above shows result from the sinus extraction system. The next step is to validate the result. Validation of the result follows a process of which comparison between the result and a gold standard image has to be firstly made. The gold standard image is the image that is manually segmented by hand which serves as a benchmark for comparison. The table below shows comparison between the manually segmented. Segmentation is considered manual when a human operator carries out both the task of recognizing the region of interest on the image and the task of manually extracting the region. The table below shows the graphical comparison of both the manual segmentation and result from sinus extraction system (SES)

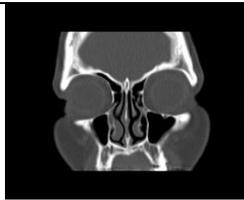
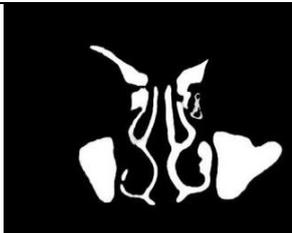
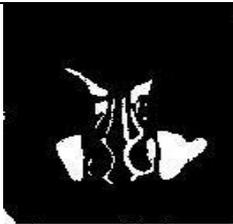
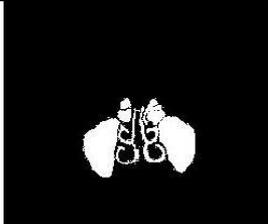
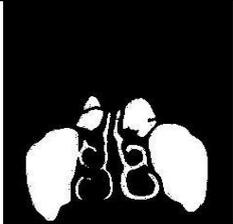
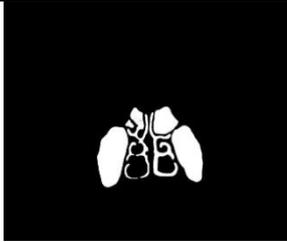
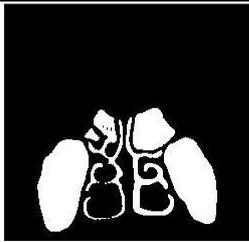
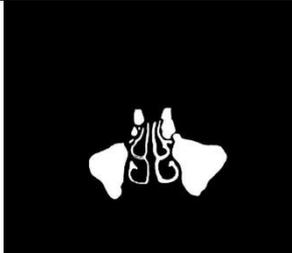
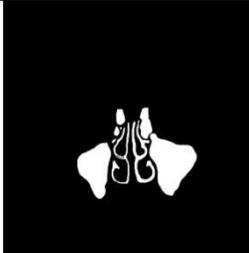
Input image	Manual Segmentation	SES Segmentation
		
		
		
		

Figure 16. Comparison of manual segmentation and SES segmentation

As suggested by Udupa et al [15], the evaluation of a segmentation algorithm is not complete without accounting for the accuracy of the method. Hence we have to measure the error percentage of the SES result and compared the result with the global threshold. This was done by writing a forward loop was in matlab to calculate the number of white pixel in the gold standard image which would be the accepted value or theoretical value and also calculate the number of white pixel in the SES which is the experiment value. The experimental value is then subtracted from the accepted value or theoretical value and divided by the theoretical

value multiply by 100. Table 1 shows the validation of the result with two methods compared. Which includes The Sinus extraction system and the global threshold which uses Otsu' method [15]. The threshold value was set to >0.2 because the SES works that threshold value.

In validating the result the first step was to first get the gold standard image to be used as a benchmark; this was done using specialist software in cutting out the region of interest from an anonymous CT scan image, four images were used, they are all shown in the table below. After creating

the gold standard image the next step was to compare the SES result with the gold standard image, this was done by using the formula below

$$PE = \frac{EV - AV}{AV} \times 100$$

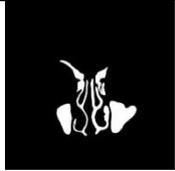
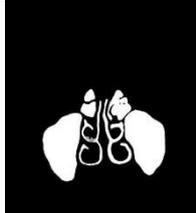
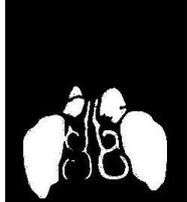
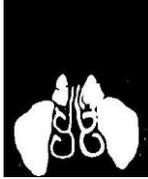
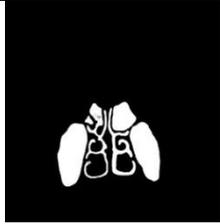
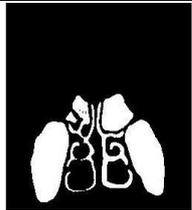
PE = Percentage Error

EV= Experimental Value

AV= Accepted Value.

Where the experimental values is the sum of white pixels from the SES and the accepted value is the sum of white pixels from the manually segmented image or the gold standard image. These values were calculated by writing a code in matlab to count the number of white pixels present SES

result and subtract it from the total number of white pixels present in gold standard image divided by the sum of white pixels from the gold standard multiply by 100 to get the percentage. In the validation process each image from the SES image and the manually segmented were measured using the formula above, the sum of white pixels in the SES image was subtracted from sum of white pixels from the manually segmented image or the gold standard image, this process was carried out on the four different images. Still on finding accuracy of the algorithm, global threshold was also applied to four images which are identical to the four images used in the SES system and also the error percentage calculated. The threshold value was set to 0.2 because the weight of the self organising map. The self organising map was trained with five classes and for 200 epochs

Gold Standard	SES Image	Error Percentage %	Global threshold > 0.2	Error Percentage %
		7.78		7.70
		3.80		3.76
		5.01		5.02

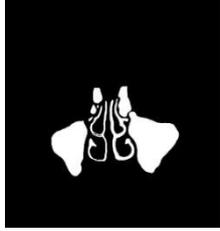
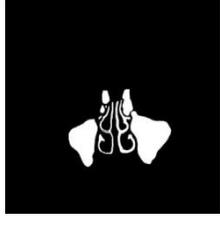
		4.12		4.08
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Table 1 Shows the Result validation.

6. Discussion and conclusion

This section shows test carried out in the process of creating an algorithm for the extraction of healthy sinus images (CT scan), the algorithm proposed in this work is effective for the extraction of healthy Ethmoidal and Maxillary Sinuses. It does not work effectively for the extraction of the frontal and sphenoid sinuses. By considering the result tabulated above, it can be seen that this work can be further extended, section 5.1 shows application of the trained network on various images, it also graphically represent what happens when the algorithm is run in matlab, figures 12-15 shows the extraction of the region of interest from the main image, various CT images were tested at this point. Figure 16 shows the graphical comparison between the manually segmented image and SES image, manually segmented images and the automatically segmented images. Table 1 shows result validation, this was done by calculating all the white pixels present in the gold standard image which serves as a benchmark, and all the white pixels present in the SES image and divided by the pixels present in the gold standard image. This was done by writing a forward loop in matlab, this was done for so many images but in this work the result for four images is shown, it also shows the comparison with global threshold which uses the Otsu's method, which uses the threshold value > 0.2 because SES works at this value.

In conclusion this work presents a new NN-based algorithm for extracting healthy sinus area (maxillary and ethmoid) from a CT scan image automatically. In this project; we examined existing method for image pre-processing, image segmentation, edge detection, image evaluation techniques and neural network. Firstly image pre-processing technique was discussed including its

short coming and advantages. Image segmentation, edge detection, image evaluation techniques and neural network were presented in full range discussing the advantages and short comings of each of them including subjective and supervised evaluation method which are currently the two most popular methods, but they have their disadvantages. Were the subjective evaluation method is time consuming and the supervised method necessitate comparison with a manually-segmented reference image which is tedious to produce.

The self organising map was trained with a sample test image for 200 setting the classes to 5, and after sampling I set the network to choose the 3rd class which seems to produce a finer resolution. The trained network was applied to a number of input images and successfully segments the image leaving the region of interest. The sinus extraction system is a combination of image processing technique and artificial neural network. The empirical results demonstrate that the sinus extraction system (SES) performs reasonably well in extracting the region of interest and also its major advantage is that it is automatic and also you have the choice of selecting any class in sampling which makes it better than global threshold.

This work can further be extended by adding more parameters in the self-organising map, like centroid and area to enable the system extract all sinus area for both the healthy and unhealthy images. Finally this work when fully developed would be useful to practising and consulting doctors by providing them with the actual region of interest. Also it would be a very useful tool for training junior doctors as a help in evaluating their clinical decision.

7. References:

1. Abed-Razzak Natesh, Prasad VS Ponnappalli, Nadar Anani, Atef EL-Kholy, Peter Norbun. Automated tool for diagnosis analysis CT Scans, AI 2001, Twenty-Seventh SGAI International Conference on Artificial Intelligence, Cambridge England 10-12 December 2007.
2. Kennedy D.W, "Functional endoscopic Sinus surgery" theory and diagnostic evaluation, archotolagol head neck surge, 111-576, 1985.
3. Shin Huha, Terence A. Ketterb, Kwang Hoon, Sohna, and Chulhee Leea. "Automated Cerebrum Segmentation from three dimensional sagittal brain MR images" computers in biology and medicine vol 32, 311-328. 2002.
4. David R. Holmes III, Brian J. Davish, Charles J. Bruce, Richard A. Robba, "3D visualization analysis and treatment of prostrate using trans-urethral ultrasound". Computerized medical imaging and graphics vol. 27, 339-349, 2003.
5. C.M. Wong, W.H. Chan, T.W. Lam, K.Y. Yip, "Surface mapping of three-dimensional objects by a planar light scanning technique" Journal of material processing technology vol 139, issue 1-3, 96-102, 2003.
6. Yan Kong, Klam Engelke, Will A. Kalendar, "Interactive 3D editing tool for image segmentation", Medical image analysis vol 8 (2004) 35-46.
7. T.F. Chan, J. Shen and L. Vese. Variational PDE models in image processing, notices of the notices Amer. Math Soc. Vol. 50, No.1, pp 14-26, 2003.
7. Lisboa PJG. A review of evidence of health benefit from artificial neural networks in medical intervention. Neural Networks, 2002. 15, p. 11-39.
9. Kohonen, T. Analysis of simple self-organising Process, Biological Cybernetics 44, 135-440, 1982a.
10. Kohonen, T. Self-Organised formation of topologically correct feature map, Biological Cybernetics 43, 59-69, 1982b.
11. Nick Jones. The Nose and Paranasal Sinuses Physiology and anatomy, Advanced Drug Delivery Reviews 51 p5-19, 2001.
12. Kass M, A Witkin, D Terzopoulos and D Snakes. Active contour models. International Journal of Computer Vision, 1(4):321- 331, 1988.
13. Pohle R and K.D. Tönnies. Segmentation of Medical Images using Adaptive Region Growing, , Vol. 4322, pp. 1337-1346, Proc. SPIE 2001.
14. Udupa J.K, LeBlanc V.R, Schmidt H, Imieloriska C.Z, Saha P.K, Grevera G.J, Zhuge Y, Molhot L.M.C.P, Jin Y. A Methodology for evaluating image segmentation algorithms. In proceedings of SPIE: Medical Imaging. The international society for optical engineering, p226-276, 2002.
15. Otsu.N "A Threshold Selection Method from Gray-Level Histogram ,," IEEE Transaction on systems, Man and Cybernetics, Vol 9, No1, pp 62-66, 1979.