

# Characterization of Temporal bone in CT Images using Texture Analysis

Zuhail Y. A. Hamd<sup>1</sup>, Suhaib Alameen<sup>2</sup>, Caroline Edward Ayad<sup>3</sup>, Mohamed E. M. Gar-Elnabi<sup>4</sup>

College of Medical Radiological Science, Sudan University of Science and Technology, Khartoum, Sudan

**Abstract:** This study concern to characterize the Temporal bone were defining to Fluid, Mucosal, Sclerotic and Soft tissues density using texture feature extraction and extract classification features from CT images. The texture analysis technique used to find the gray level variation in CT images. analyzing the image with Interactive Data Language IDL software to measure the grey level variation of images. The results show that texture analysis give classification accuracy of temporal bone to fluid 86.3%, mucosal 98.2%, sclerotic 99%, While the soft tissue density showed a classification accuracy 92.2%. the overall classification accuracy of temporal bone area 93.6%. These relationships are stored in a Texture Dictionary that can be later used to automatically annotate new CT images with the appropriate temporal bone area names.

**Keywords:** Temporal bone, Chronic Otitis Media, Computed Tomography, Texture Analysis

## 1. Introduction

Chronic otitis media (COM) is a longstanding inflammation of the middle ear cleft without reference to a etiology or pathogenesis. Due to the strategic location of the tympanomastoid compartment, separated from the middle and posterior cranial fossa by the thinnest of bony partitions, otitis media has the potential for intracranial extension [1].

Hence, it becomes very important to know the location and extent of the disease before proceeding to surgical treatment. Radiological examination of the temporal bone helps us to achieve this objective. It is important to differentiate between the two types of COM: The chronic mucosal disease and the chronic otitis media with cholesteatoma because of higher risk of complications associated with the cholesteatoma group which can lead to life threatening conditions. Early recognition of the disease is important to adopt a surgical procedure to save the patient from loss of hearing and to prevent grave intracranial complications. The present work, has been undertaken to study the role of High Resolution Computed Tomography (HRCT) of temporal bone as a diagnostic modality in COM [1].

The computed tomography (CT) of temporal bones demonstrates with large accuracy the presence of abnormal tissue in the middle ear, but cannot define whether this tissue with soft parts density represents or not the presence of a cholesteatoma. [2]

The definition of COM is based on clinical and pathological features. COM is traditionally characterized by the presence perforations, cholesteatoma, recurrent ear discharge, and hearing loss. Histopathologically it is defined by the presence of middle ear inflammation, associated with irreversible tissue damage, regardless of the presence of tympanic membrane perforations [3]. The disease often evolves in a continuum. Abnormalities that at first caused mild or minimal symptoms, such as simple retractions, for example, can progress to severe

changes, such as retraction pockets and destructive cholesteatomas.

This continuum model [4,5,6] explains the development of COM in a progressive manner. According to this theory, effusion, perforations, and cholesteatomas represent different pathological stages of the same disease.

The evolution of this continuum can be seen in the contralateral ear (CLE). When tubal dysfunction is the trigger of COM, there is a high probability of impairment of both ears, although in different intensity. Some studies point to a tendency of bilateral involvement in inflammatory pathologies of the middle ear.

Computed tomography (CT) is an excellent method to visualize bone and pneumatized spaces. It is therefore the best diagnostic method to evaluate the involvement of temporal bone structures resulting from chronic inflammation.

There are well-documented findings of COM in CT studies [7]. Modern techniques of helical image acquisition and high-resolution cuts allow the evaluation of smaller structures more accurately.

A comprehensive understanding of the role of the CLE in the evaluation of patients with COM is essential, especially when viewing otitis media from a continuum perspective. We believe that the study of the CLE can provide clues to the pathophysiology of the primary ear disease (ear with full-blown disease), serve as a parameter of tubal function, and contribute to the therapeutic planning.

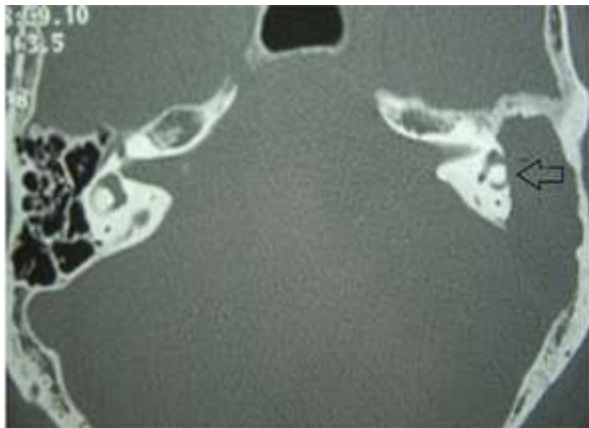
CT scanning excels in the evaluation of bone and air space anatomy and disorders. Because CT scans are more accurate in identifying many soft tissue abnormalities and are much less prone to artifacts, they have largely replaced polytomography, there is also less radiation to the lens with CT scans than with

polytomography. CT has the advantage of producing images with higher contrast and a better spatial resolution [8].

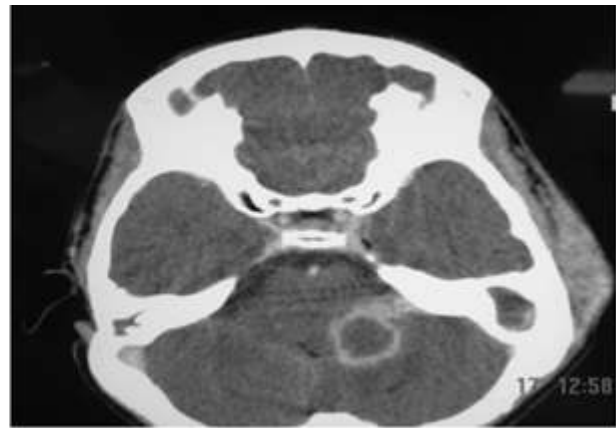
Computed tomography (CT) is necessary for all patients suspected of having complications of otitis media. CT scan is a reliable method for studying the status of the mastoid air cell system, middle ear, internal auditory meatus (IAM), and also intracranial complications of otitis media. [9,10] Treatment of COM is surgical (tympanoplasty with or without mastoidectomy). Having enough knowledge of the middle ear before the surgery can help the surgeon choose the

optimal surgical procedure and achieve appropriate results [11].

Evaluation of the temporal bone is difficult because of its complex anatomy containing multiple small structures within a moderately compact area. Further information revealed by three-dimensional images gives a better understanding of temporal bone anatomy and advances the capability to evaluate related disease, thus optimizing surgical planning [12].



(A)



(B)

**Figure:** (A) show temporal bone CT, axial view, the arrow shows erosion of the lateral semicircular canal on the left. (B) brain CT with contrast, axial view and soft tissue window, show cerebellar abscess on the left

## 2. Statistical Methods

**First Order Statistics:** FOS can be used as the most basic texture feature extraction methods, which are based on the probability of pixel intensity values occurring in digital images. The parameters in the following statistical formulas are  $x_i$ , the intensity value of pixel  $i$ ,  $N$ , the total number of pixels,  $\max V$ , the maximum intensity value within a patch and  $H_i$ , the histogram of an image patch.

**Mean:** Calculates the mean intensity value of all pixels. In Matlab the function  $\mu = \text{mean2}(IP)$  can be used to compute this feature.

$$\mu = \frac{1}{N} \sum_{i=1}^N x_i$$

### Standard Deviation

The standard deviation of all the intensity values of a patch is used as a texture feature. The corresponding Matlab function is  $\sigma = \text{std2}(IP)$ .

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - \mu)^2}$$

### Coefficient of variation

The coefficient of variation can be seen as the relative standard deviation. It is calculated by dividing the standard deviation with the mean value.

$$c_v = \frac{\sigma}{\mu}$$

### Skewness

Another statistical measure which is used for texture analysis is skewness. It measures the symmetry of a distribution curve of pixel intensity occurrences as seen in a histogram. The function

$\gamma_1 = \text{skewness}(IP)$  can be used to compute the skewness in Matlab.

$$\gamma_1 = \frac{\frac{1}{N} \sum_{i=1}^N (x_i - \mu)^3}{\left(\frac{1}{N} \sum_{i=1}^N (x_i - \mu)^2\right)^{\frac{3}{2}}}$$

### Kurtosis

The kurtosis measures the flatness of a histogram relative to a normal distribution. A curve has a high kurtosis when it has a clear peak close to the mean value. The Matlab function for the kurtosis is  $\gamma_2 = \text{kurtosis}(IP)$ .

$$\gamma_2 = \frac{\frac{1}{N} \sum_{i=1}^N (x_i - \mu)^4}{\left(\frac{1}{N} \sum_{i=1}^N (x_i - \mu)^2\right)^2} - 3$$

**Entropy**

The entropy of a gray-scale image is a measure of intensity value randomness. It is calculated from the histogram counts of an image giving a probability of certain pixel values occurring in the image.

$$s = - \sum (p \cdot \log_2(p))$$

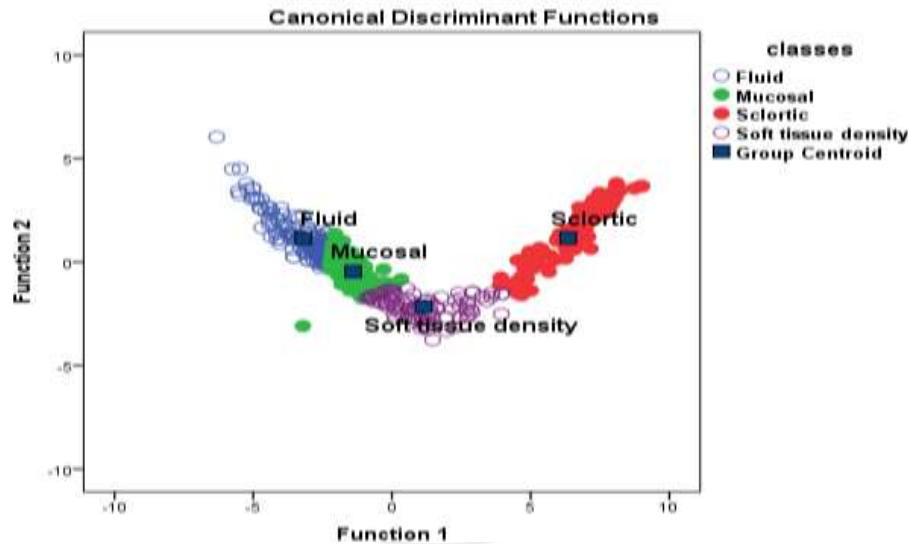
**2.1 Materials: CT scanner machine**

GE 8 slice MDCT scan. **Scanning parameters:** 120-140 kV, 200 -220 mAs. **tubespecification:** focal spot 0.6mm \*0.6mm and anode heat dissipation 400kuH/min, anode heat storage capacity 4.0 MHU. **Gantry specification:** Rotation speed 360° in 0.30, 1, 1.5 second, tilt +/-30 ° and aperture 70 cm. **Detector specification :** Scan type eight (option) ,spiral or axial, slice thickness 0.5, 1.0, 1.5, 3.0, 5.0 and 10 mm, scan mode 0.50:1 /1.5:1. Algorithm (option) standard ,soft tissue ,bone and edge enhancement , matrix 512\*512 and 20 cm field of view.

**2.2 Technique and Protocol**

Scan to evaluate the organ of hearing and balance was obtained. Thin slices without overlapping were used to ensure optimal resolution, the whole skull was not imaged, and just the required part of the temporal bone was included. The two temporal bones images are magnified and imaged separately. This to make possible differentiation between small structures like the ossicles, cochlea and semicircular canals. CT scans were performed including protocol of axial images from the area of temporal bone with patient in supine position, head first. Reconstruction used to obtain coronal views of temporal bone. No preparation for patient who's undergone CT temporal bone was done. Analyzing the images with Interactive Data Language IDL software to measure the grey level variation of CT images, classify the CT temporal bone to Fluid, Mucosal, Sclerotic and Soft tissues density the features of the classified regions of the whole images (as raw data) were classified further using linear discriminate analysis.

**3. Results**



**Figure 1:** Scatter plot demonstrates the distribution of four Classes according to their textural feature using linear discriminate analysis functions

The classification showed that the temporal bone was classified well from the rest of the tissues although it has characteristics mostly similar to surrounding tissue.

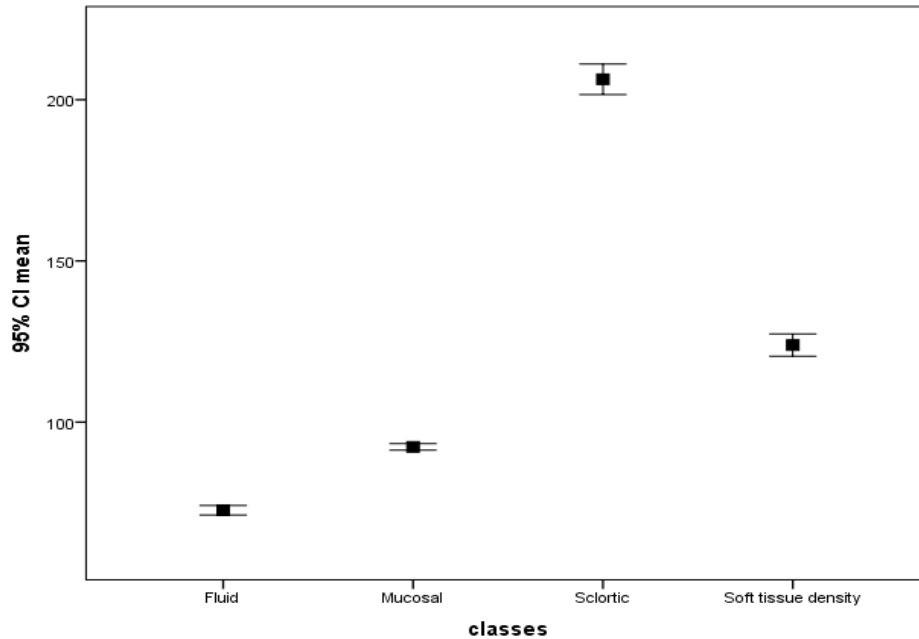
**Table 4-1:** A confusion matrix shows the classification accuracy of the original classes versus the predicted membership according to linear discriminant functions (multiple linear regression equation)

Classes		Predicted Group Membership				Total
%	Original groups	Fluid	Mucosal	Sclerotic	Soft tissue density	
	Fluid	86.3%	13.8%	0.0%	0.0%	100.0%
	Mucosal	0.0%	98.2%	0.0%	1.8%	100.0%
	Sclerotic	0.0%	0.0%	99.0%	1.0%	100.0%
	Soft tissue density	0.0%	7.8%	0.0%	92.2%	100.0%

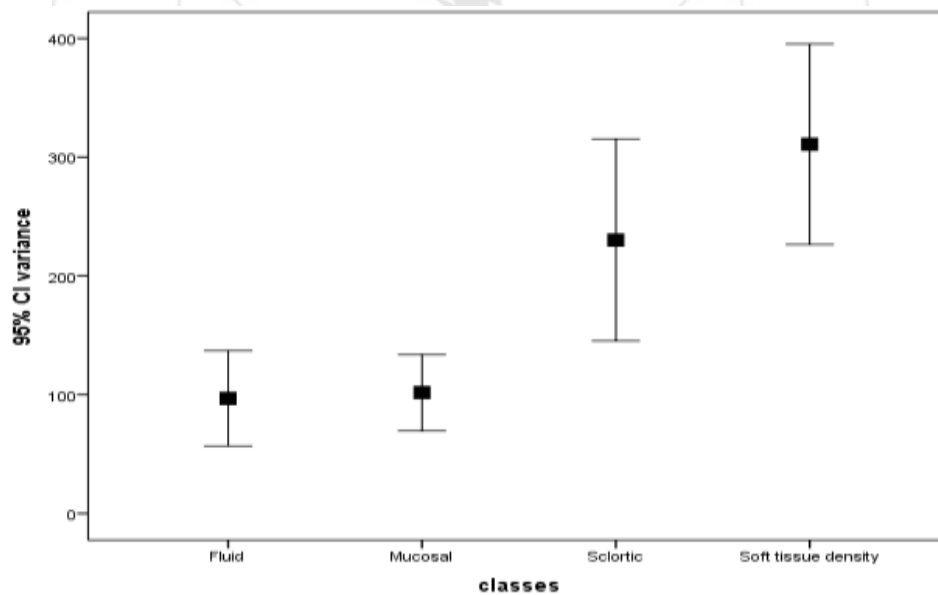
93.6% of original grouped cases correctly classified.

Table (1) show classification score matrix generated by linear discriminate analysis and the overall classification accuracy of temporal bone 93.6%, were the classification accuracy of

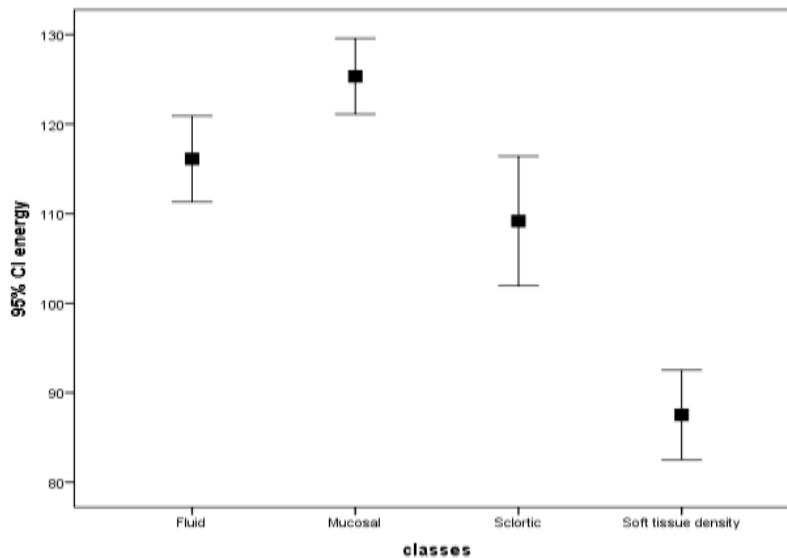
fluid 86.3%, mucosal 98.2%, sclortic 99%, While the soft tissue density showed a classification accuracy 92.2%.



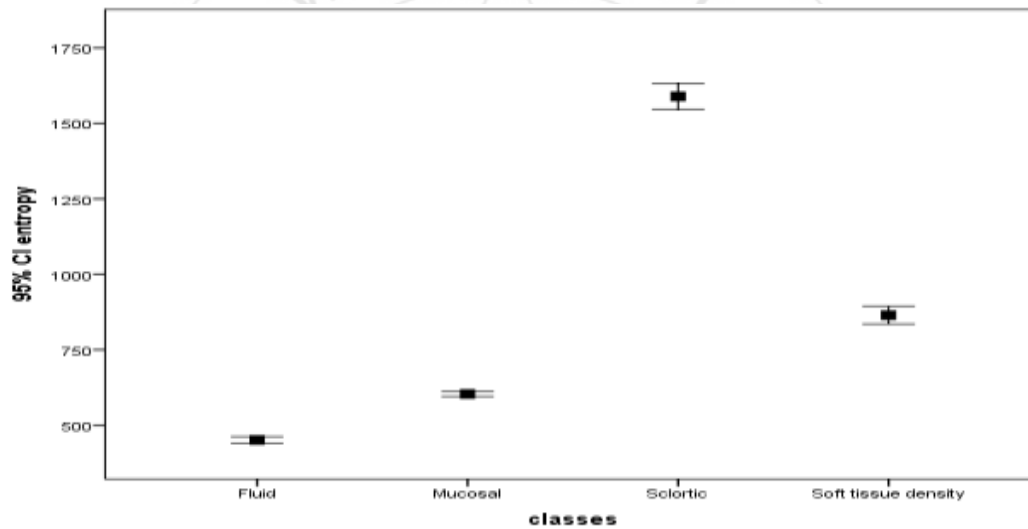
**Figure 3:** Show error bar plot for the CI mean textural features that selected by the linear stepwise discriminate function as a discriminate feature where it discriminates between all features. From the discriminate power point of view in respect to the applied features the mean can differentiate between all the classes successfully.



**Figure 4:** Show error bar plot for the CI variance textural features that selected by the linear stepwise discriminate function as a discriminate feature where it discriminates between all features.



**Figure 4** show error bar plot for the CI energy textural features that selected by the linear stepwise discriminate function as a discriminate feature where it discriminates between all features.



**Figure 4:** Show error bar plot for the CI entropy textural features that selected by the linear stepwise discriminate function as a discriminate feature where it discriminates between all features.

#### 4. Conclusion

The classification processes of CT Temporal bone were defining the otitis media to Fluid, Mucosal, Sclerotic and Soft tissues density and carried out using Interactive Data Language (IDL) program as platform for the generated codes. The result of the classification showed that the temporal bone areas were classified well from the rest of the tissues although it has characteristics mostly similar to surrounding tissue.

Several texture features are introduced from *FOS* and the classification score matrix generated by linear discriminate analysis and the overall classification accuracy of temporal bone area classify to fluid 86.3%, mucosal 98.2%, sclerotic 99%, While the soft tissue density showed a classification

accuracy 92.2%. The overall classification accuracy of temporal bone area 93.6%.

Using Linear discrimination analysis generated a classification function which can be used to classify other image into the mention classes as using the following multiregression equation;

*Fluid, Mucosal, Sclerotic and Soft tissues density*

$$\text{Fluid} = (\text{mean} \times 23.7) + (\text{variance} \times 0.006) + (\text{energy} \times -0.099) + (\text{entropy} \times -2.703) - 247.54$$

$$\text{Mucosal} = (\text{mean} \times 26.1) + (\text{variance} \times 0.006) + (\text{energy} \times -0.109) + (\text{entropy} \times -2.97) - 303.93$$

$$\text{Sclerotic} = (\text{mean} \times 26.7) + (\text{variance} \times 0.007) + (\text{energy} \times -0.104) + (\text{entropy} \times -2.97) - 387.66$$

$$\text{Soft tissues density} = (\text{mean} \times 28.4) + (\text{variance} \times 0.009) + (\text{energy} \times -0.17) + (\text{entropy} \times -3.22) - 362.83$$



## References

- [1] Chakenahalli p. Nanjaraj, Pradeep Hagalahalli Nagarajegowda, Vijay Prakash Kannan, Pradeep Kumar Chandanur Nagarajaiah, chronic otitis media: high resolution computed tomographic evaluation of the temporal bone with surgical correlation, j. evid. based med. healthc., pISSN- 2349-2562, eISSN- 2349-2570/ vol. 3/issue 40/may 19, 2016, page 1955-1962.
- [2] Anelise Abrahao SalgePrata, Marcos Luiz Antunes, Carlos Eduardo Cesario de Abreu, Ricardo Frazatto, Bruno Thieme Lima, Comparative Study Between Radiological and Surgical Findings of Chronic Otitis Media Intl. Arch. Otorhinolaryngol., São Paulo - Brazil, v.15, n.1, p. 72-78, Jan/Feb/March - 2011. Pages 72-78.
- [3] Costa SS, Dornelles CC, Netto LFS, Braga MEL. Otites médias. In: Costa SS, Cruz OLM, Oliveira JAA. Otorrinolaringologia: princípios e prática. 2ª ed. Porto Alegre: Artmed; 2006. p.254-73.
- [4] Paparella MM. Current concepts in otitis media. Henry Ford Hosp Med J. 1983;31(1):30-6.
- [5] Yoon TH, Paparella MM, Schachern PA, Lindgren BR. Morphometric studies of the continuum of otitis media. Ann Otol Rhinol Laryngol Suppl. 1990;148:23-7.
- [6] Paparella MM, Kim CS, Goycoolea MV, Giebink S. Pathogenesis of otitis media. Ann Otol Rhinol Laryngol. 1977;86(4 Pt 1):481-92.
- [7] Lemmerling MM, De Foer B, Vande Vyver V, Verduyck JP, Verstraete KL. Imaging of the opacified middle ear. Eur J Radiol. 2008;66(3):363-71. <http://dx.doi.org/10.1016/j.ejrad.2008.01.020>
- [8] Kangsanarak J, Foonant S, Ruckphaopunt K, Navacharoen N, Teotrakul S (1993) Extracranial and intracranial complications of suppurative otitis media: report of 102 cases. J Laryngol Otol 107:999-1004
- [9] Berman S. Management of acute and chronic otitis media in pediatric practice. *Curr Opin Pediatr.* 1995;7(5):513-22. [PubMed:8541950].
- [10] Blevins NH, Carter BL. Routine preoperative imaging in chronic ear surgery. *Am J Otol.* 1998;19(4):527-35. [PubMed: 9661767]
- [11] Chole R, Sudhoff H. Chronic otitis media, Mastoiditis and Petrositis. In: Cummings C, Fint PW, Harker LA, Haughey BH, Richardson MA, Robbins KT, et al., editors. *Otolaryngology Head and Neck Surgery*. 4th ed. Philadelphia: Elsevier; 2005.
- [12] Lin YS, Lin LC, Lee FP, Lee KJ. The prevalence of chronic otitis media and its complication rates in teenagers and adult patients. *Otolaryngol Head Neck Surg.* 2009;140(2):165-70. doi:10.1016/j.otohns.2008.10.020. [PubMed: 19201282]