Biomedical Signal Processing and Control 39 (2018) 117–129

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

Research Paper

# A novel segmentation of cochlear nerve using region growing algorithm

S. Jeevakala[a,*], A. Brintha Therese[a], Rangasami Rajeswaran[b]

[a] School of Electronics Engineering, VIT University, Chennai, India
[b] Department of Radiology and Imaging Sciences, Sri Ramachandra University, Chennai, India

ARTICLE INFO

*Article history:*
Received 29 November 2016
Received in revised form 6 May 2017
Accepted 20 July 2017
Available online 8 August 2017

*Keywords:*
Cochlear nerve
Internal auditory canal
Sensorineural hearing loss
Cochlear implant
Region growing
Automatic measurement
Magnetic resonance(MR) image

ABSTRACT

Sensorineural hearing loss is a hearing impairment which occurs when there is damage to the inner ear, or to the nerve pathways from the inner ear to the brain. Cochlear implants have been developed to benefit children with bilateral or unilateral Sensorineural hearing loss. A very small or absence of cochlear nerve precludes successful outcome of cochlear implant surgery. Hence, segmentation and measurement of the cochlear nerve support the surgeon's decision to predict a normal or poor outcome of the cochlear implant. For this purpose, a modified region growing segmentation algorithm is proposed that segments the cochlear nerve region accurately. The segmentation accuracy is evaluated using parameters like Jaccard, Dice, False Positive Dice, and False Negative Dice. The segmented region is measured and evaluated using long diameter, short diameter, and cross-sectional area. The statistical analyses of intra/inter-observer correlation and limits of agreement are performed on a cross-sectional area of the cochlear nerve to investigate the reproducibility of the automated measurement.



## 1. Introduction

Sensorineural hearing loss (SNHL) is a hearing impairment resulting from a pathological condition in the inner ear or along the auditory nerve (VIII cranial nerve) pathway from the inner ear to the brainstem. Early diagnosis and its treatment are critical in optimizing speech and language development, academic achievement, social and emotional development of children with congenital hearing loss [1]. Cochlear implant (CI) is an effective treatment option for pediatric patients with congenital SNHL [2]. Measurement of the size of the cochlear nerve (CN) helps the surgeon's to predict outcome after CI [3]. Also, the size of the CN diameters will be significant to clarify pathological condition or consolidate the diagnosis of disorders of the CN [4].

In the past, several studies have reported the importance of the normal size of the CN [2,4,5,6–8]. Herman et al. [9] speculated on the difference in CN size between post lingually deafened patients and those with normal hearing, by the use of magnetic resonance (MR) images. Sildirogula et al. [10] evaluated the mean cross-sectional area (CSA) of CN in patients with SNHL using three-dimensional constructive interference steady state (3D- CISS) MR images and suggested that there is no significant difference in CN size in acquired SNHL. Kim et al. [11] measured the size of CN and reported that CN size is positively correlated with auditory performance after CI in post lingually deaf patients. Absence or reduced size of the CN have been described in relationship with SNHL. Delineation of CN integrity might be critical for analysis and management of SNHL [12]. The absence of the CN is considered a total contraindication for CI since a hypoplastic CN is a relative contraindication for CI. For patients with hypoplastic CN, the CN size is important before CI surgery as the implant outcome is better when the size of the CN is near normal [13]. Therefore, considering the facts, the size of CN is the critical point to decide CI in patients with congenital or acquired SNHL.

To measure the CN size, an experienced radiologist analyzes the MR images of the inner ear, slice by slice. Since the CN is smaller in the order of 1 $mm^2$ calculating CSA manually is monotonous, time-consuming, and prone to error. In contrast to the manual segmentation and measurement, computer-assisted algorithms are faster, and can, simplify the subsequent decisions by the otolaryngologist, and thereby provide a better diagnosis. Hence, for computer analysis of 3D-CISS images, an appropriate processing ought to be performed in developing an automatic algorithm for CN segmentation and measurement.

Segmentation of the CN in MR image from the inner ear is a significant issue, as well as measurement. In particular, segmenting

* Corresponding author at: School of Electronics Engineering, VIT University, Chennai, India.
*E-mail addresses:* jeevakala.s2013@vit.ac.in, jeevakala.a@gmail.com (J. S.).

http://dx.doi.org/10.1016/j.bspc.2017.07.014
1746-8094/

the correct size of CN is the vital reason for successful measurement of CN. The computer-aided algorithm must aid the radiologists in not only CN detection task but also in CN segmentation and measurement. Such computer-aided algorithm requires CN edge to be identified as precisely as possible, because, the main characteristic of CN is its edges, which are preserved to influence the diameter. In order to simplify the segmentation process, a region-of-interest (ROI) is cropped from the inner ear MR image. Pixels with the lowest intensity in the ROI correspond to nerves in the internal auditory canal (IAC). Recently, the visualization of the inner ear was performed based on Otsu segmentation to study the benign paroxysmal positional vertigo (BPPV) [14]. The Otsu segmentation approach uses the intensity histogram to split the region into two or more groups [15]. As the threshold selected based on the variance of pixels is large, it has failed to segment CN and its edges. To the best of our knowledge, no method was proposed to segment and measure the dimension of CN from 3D-CISS MR images. The separation of lower intensity pixels in CN from higher intensity surroundings implies a region growing method to segment the CN from ROI [16]. The region growing method is simple, computationally less intensive and can segment regions with similar properties and generate a connected region based on the initial seed points and threshold [17]. Many region growing segmentation methods have been discussed based on the seed point and threshold determination. Some of the recent studies are discussed as follows. The seeded region growing (SRG) algorithm by [18] determined seed points based on centroids between the adjacent edges. The major disadvantage of this method was that the seed points were over generated. The boundary segmentation based on the region growing method by [16] selects the brightest pixels as seed points. Then the threshold was done experimentally to segment the ROI from the image. Adopting a constant threshold for all the image resulted in, over- or under-segmentation of images. The local seeded region growing (LSRG) was explained by [19], determined the seed points and similarity measures based on the local and global information (mean and standard deviation) of the image. Also, the different thresholds were selected and tested to produce a better segmentation of the ROI from the image. However, it is a time-consuming procedure to test different thresholds on different images. These drawbacks are overcome by Kernel Density Estimation (KDE) as it considers only the maximum intensity of the pixel in ROI to discriminate the structure and shape of subtle tissues/organs. In this work, a CN segmentation is introduced, which depends on the region growing method, with the combined development of adaptive seed points on the region growing and different threshold were selected to segment the correct size of the CN. This segmentation approach will assist the radiologist in segmenting the CN and quantification of the nerve to its correct size.

This paper is organized as follows: Section 2 describes the proposed method consisting of Datasets, pre-processing, CN segmentation, CN measurement, and metrics and scoring. Section 3 discusses the experimental results of segmentation and measurement, Section 4 deals with discussion of the proposed algorithm and finally, Section 5 gives the conclusion.

## 2. Methods

The proposed method begins with pre-processing. The MR image is de-noised to preserve contrast and edge information of subtle structure. Next, the modified region growing method with adaptive seed point and the threshold are employed to segment the CN from the ROI in an image. Then, the CN measurement is obtained from the segmented output, by multiplying the number of pixels in the CN region and the voxel size.

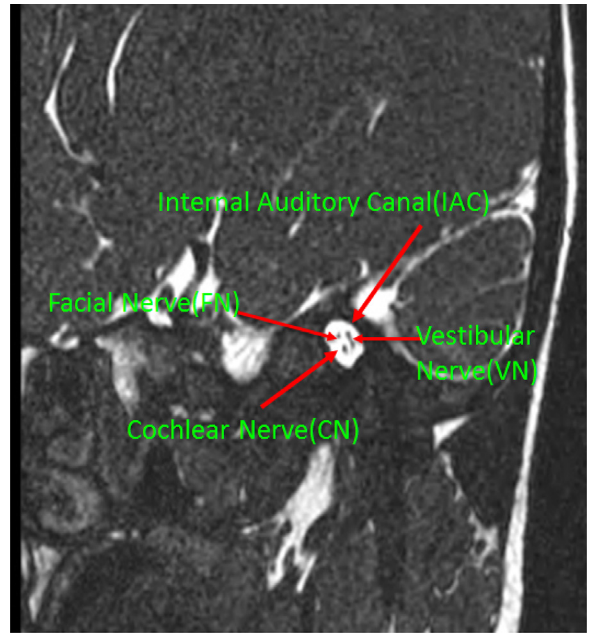


**Fig. 1.** The oblique sagittal 3D-CISS MR image showing CN.

### 2.1. Data

The input data set are obtained using 1.5 Tesla MRI scanners (Siemens Avanto, Erlangen) from the Sri Ramachandra Medical University. Ethical clearance was obtained for the study, and the images of 20 patients during July 2014 to July 2015 are analyzed. The parameters for the 3D-CISS sequence are Field of View (FOV) 120 mm, Slice Thickness 0.9 mm, Voxel Size $192 \times 256$, Repetition Time (TR) 2.79 ms, Echo Time (TE) 6.62 ms. Initially, axial CISS images of the inner ear are obtained. Subsequently, oblique sagittal images are obtained perpendicular to the VIII cranial nerve for each side. The oblique plane sagittal view imaging can be promptly recognized in mid-IAC (Fig. 1). At the oblique part of IAC, the vestibular nerves (VN) lie in the posterior portion, the facial nerves (FN) lie in the anterior superior portion, and the CN lie in the anterior inferior portion of the canal [6].

### 2.2. Pre-processing

The pre-processing step aims at reducing the noise and increasing the contrast level between CN and other background tissues. The MR images are often corrupted by signal-dependent Rician noise, which deteriorates the image quality and segmentation of subtle tissues/organs. Since Rician noise is signal dependent, it creates a random fluctuation and introduces signal dependent bias to the data, which in turn reduces the image contrast [20]. In this present study, a non-Local means based de-noising technique [21] is employed to reduce the effects of noise while preserving subtle nerves edges of tissues/organs. Fig. 2 shows the results of non-local means filter method of denoising. Fig. 2(a) shows the original image with very slight noise and Fig. 2(b) shows the denoised image with reduced noise and well-preserved border and shape of the CN. Then, the resolution of ROI image is enhanced using Lanczos-2 kernel [22] to smooth the nerve edges adequately. The interpolated ROI image without denoising is shown in Fig. 2(c). The edges and shape of the tissues are blurred due to noise at its edges, whereas the interpolated ROI image with denoising (Fig. 2(d)) shows a well-preserved border and shape of the tissues. The edge and structural preservation of the ROI images are also validated using the two indexes: Feature similarity index (FSIM) [23], and Structural sim-