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Abstract. Cochlear implants (CIs) are standard treatment for patients who experience sensorineural hearing loss. Although these devices have been remarkably successful at restoring hearing, it is rare that they permit to achieve natural fidelity and many patients experience poor outcomes. Our group has developed image-guided CI programming techniques (IGCIP), in which image analysis techniques are used to locate the intracochlear position of CI electrodes to determine patient-customized settings for the CI processor. Clinical studies have shown that IGCIP leads to significantly improved outcomes. A crucial step is the localization of the electrodes, and rigorously quantifying the accuracy of our algorithms requires dedicated datasets. We discuss the creation of a ground truth dataset for electrode position and its use to evaluate the accuracy of our electrode localization techniques. Our final ground truth dataset includes 30 temporal bone specimens that were each implanted with one of four different types of electrode array by an experienced CI surgeon. The arrays were localized in conventional CT images using our automatic methods and manually in high-resolution μ CT images to create the ground truth. The conventional and μ CT images were registered to facilitate comparison between automatic and ground truth electrode localization results. Our technique resulted in mean errors of 0.13 mm in localizing the electrodes across 30 cases. Our approach successfully permitted characterizing the accuracy of our methods, which is critical to understand their limitations for use in IGCIP. © 2018 Society of Photo-Optical Instrumentation Engineers (SPIE) [DOI: 10.1117/1.JMI.5.3.035001]

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1 Introduction

Cochlear implants (CIs) are neural prosthetics that are used to treat sensory-based hearing loss. With CIs, an array of electrodes is implanted into the cochlea to directly stimulate auditory nerves (see Fig. 1). Each electrode is activated when sound detected by a microphone and processor worn behind the ear contains the specific frequency range that is assigned to that electrode. The electrodes, between 12 and 22 depending on the manufacturer, are situated on a linear array that is surgically inserted into the cochlea. The electrodes stimulate spiral ganglion (SG) auditory nerve fibers in order to create the sensation of sound. Deeper electrodes are activated for lower frequency sounds, and vice versa, as this matches the natural tonotopic organization of the auditory nerves in the cochlea¹ [see Fig. 1(c)]. Studies have shown a correlation between hearing outcomes and intracochlear locations of CI electrodes.^{2–6} The spread of electrical current in the cochlea when electrodes are activated creates broad stimulation patterns in the auditory nerves. Electrodes that are situated further from the neural stimulation sites create broader stimulation patterns. When multiple electrodes have highly overlapping stimulation patterns, an artifact called channel interaction occurs that negatively affects hearing outcomes^{7,8} [see Fig. 1(d)]. This is because in natural hearing, activation of nerve groups occurs when specific frequencies are present in the sound, whereas channel interaction leads to nerve groups being activated in response to multiple frequency bands. Channel interaction can

be alleviated by deactivating the electrodes that potentially cause the interaction.⁹

In the last few years, our group has been focusing on developing an image-guided cochlear implant programming (IGCIP) strategy by using CT image analysis techniques.¹⁰ Recent clinical studies we have performed have indicated that by using our IGCIP, hearing outcomes can be significantly improved.^{9,11} In IGCIP, we detect electrodes that may cause channel interaction based on their intracochlear locations with respect to auditory nerves and we deactivate them. A crucial step when detecting whether channel interaction is occurring is to identify the intracochlear locations of individual electrodes.^{12,13} However, the intracochlear locations of CI electrodes are usually unknown because: (1) during the surgery, an electrode array is blindly threaded into the cochlea by a surgeon. The path of the insertion is only guided by the walls of the spiral-shaped intracochlear cavities. (2) The cochlea is difficult to view in postimplantation imaging. While CT is the best available clinical modality for this purpose, the small size and spacing between electrodes and the limited resolution of clinical CTs can make it difficult to localize the electrodes, and artifacts created by the presence of the electrode array obscure cochlear anatomy, making it difficult to identify the position of the electrodes relative to anatomical structures. In IGCIP, we first determine the intracochlear locations of CI electrodes by registering a preimplantation CT, where the intracochlear structures are segmented, to a postimplantation CT, where the electrodes can be identified. Then, we use an automatic electrode configuration selection method¹⁴ to select a set of active electrodes that do not have channel

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Fig. 1 (a) and (b) A CI electrode array superimposed on the scala tympani (red) and scala vestibuli (blue) cavities of the cochlea in posterior-to-anterior and lateral-to-medial views, respectively. (c) The scalae and neural activation region color coded by place frequency in Hz. (d) Overlapping stimulation patterns from the implanted electrodes as they stimulate neural regions.

interaction. Several automatic methods for localizing intracochlear structures and the electrodes have been proposed by our group.^{12,13,15–19} However, the methods we have developed for localizing the CI electrodes have only been compared to clinical CT-based manual localizations. For CI electrodes, CT images are imperfect references. Indeed, in CT images the partial volume artifact is known to limit how accurately small-sized objects can be identified. The typical size of the CI electrodes is $\sim 0.3 \times 0.3 \times 0.1 \text{ mm}^3$, which is often smaller than the size of a voxel in clinical CTs. Thus, accurate localization of CI electrodes in clinical CTs is difficult, even with care and expertise. Image artifacts such as beam hardening artifacts also complicate the process for generating ground truth localization results from clinical CTs. Compared to clinical CTs, μ CTs are a better option for the generation of ground truth electrode localizations. This is because in μ CTs, beam hardening artifacts and partial volume artifacts still exist, but, due to the drastically higher

resolution of μ CT images, the artifacts are not severe enough to make the electrode localization process difficult for experts [shown in Figs. 2(b) and 2(c)]. Thus, in this study, we have developed a more accurate ground truth dataset for electrode position based on high-resolution μ CT images and use it to evaluate the accuracy of our electrode localization techniques. Characterizing the accuracy of our methods is critical to understand their limitations for use in IGCIIP. We also are using our electrode localization techniques to evaluate the correlation between electrode position and hearing outcomes with the standard-of-care CI programming approach in a large-scale study. Large-scale analysis of this correlation has been difficult due to the challenges in CI imaging discussed above. While some correlations are known based on small scale studies, e.g., there is a relationship between scalar positioning of the electrodes, i.e., whether all electrodes sit within the scala tympani (ST) cavity of the cochlea or whether some electrodes are located in

Fig. 2 (a) The conventional CT, (c) registered μ CT, and (b) a checkerboard combination of the two. (d) The isosurface of the highest intensity voxels of the CT (brown) and μ CT (green). (e) The CT isosurface with the automatically (yellow) and manually (red) localized electrodes from the CT and μ CT, respectively.

the scala vestibuli (SV) cavity [see Fig. 1(b)];^{4–6} other positional factors have been less-well studied, and large-scale analysis is needed to better characterize how known and yet unknown positional factors impact outcomes. To use our automated methods to study this correlation, it is critical to characterize how accurately they can localize the electrodes to understand the limitations of our analyses.

Prior to our study, several groups had leveraged μ CTs of temporal bone specimens for evaluation of CI image analysis-related techniques. Skinner et al. proposed an atlas-based method for cochlear anatomy localization, where the CT of an atlas cochlea was rigidly registered to a new patient CT, and the registered atlas μ CT and histological imaging were used to localize anatomical structures in the patient. In Noble et al.,¹⁵ we expanded on this idea and used a set of μ CTs from six specimens to construct a so-called active shape model of cochlear anatomy that describes nonrigid cochlear variations and can be nonrigidly registered to new patient CTs to localize cochlear anatomy. We have since expanded our library to 10 specimens. Demarcy²⁰ similarly used μ CTs to model variances in cochlea shape. Since all of these studies focus on cochlear anatomy, they used μ CTs of nonimplanted specimens, and thus these datasets could not be used for evaluating CI electrode localization methods. Bennink et al.²¹ developed a semiautomatic electrode localization method and evaluated it against a CT-based ground truth, rather than a high-resolution modality such as μ CT. Gerber et al.²² created a dataset consisting of clinical CTs and μ CTs for the study of the statistical shape of the cochlea and variance in electrode array insertions. Their dataset included only four postimplantation CT- μ CT pairs, which would be of limited use for evaluation of the accuracy of the automatic electrode localization methods given the wide intersubject variability in electrode appearance.

In this paper, we present the creation of a highly accurate ground truth dataset for the validation of our automatic CI electrode localization methods in CTs. The final dataset we create consists of conventional CTs, registered high-resolution μ CTs, and ground truth localizations of individual electrodes of 30 temporal bone specimens implanted with four different types of CI electrode arrays. This dataset can be used to evaluate different CT-based electrode localization methods in the future. In Sec. 2, we discuss the creation of our dataset, the generation of ground truth electrode locations, and the validation approach that uses the created ground truth to evaluate an existing electrode localization method in IGCIP in detail. In Sec. 3, we present the results of our validation study on our ground truth dataset. In Sec. 4, we summarize the contribution of this work and discuss future work.

2 Methods

2.1 Ground Truth Dataset Creation

In this study, we start with an initial dataset including 35 temporal bone specimens that were each implanted with one of four different CI electrode array models by an experienced CI surgeon. Twenty were implanted with an array type that our method has been trained to localize, and the remaining 15 were implanted with three array types (five specimens each) that the algorithm was not trained on to see how well the method generalizes to new types of arrays without retraining the parameters. Each specimen underwent pre- and postimplantation CT imaging and postimplantation μ CT imaging. The typical voxel

size for CT images and μ CT images are $\sim 0.2 \times 0.2 \times 0.3 \text{ mm}^3$ and $0.019 \times 0.019 \times 0.019 \text{ mm}^3$, respectively.

The ground truth electrode positions were localized manually in the high-resolution μ CT images by two experts independently. The two experts were RFL (an experienced CI surgeon) and YZ (an image processing expert with over 4 years of experience in CI image analysis). Each of the two experts generated a manual localization, which includes a localization for each electrode in the array, for each case repeatedly until the addition of new manual localizations changed the position of each electrode in the expert's average localization by no more than 0.05 mm, indicating the expert's localizations converged to a result that is very close to the best estimate of the electrode location achievable using the μ CT image. For YZ and RFL, the averaged manual localizations on μ CTs are denoted as GL_1 and GL_2 , respectively. The final ground truth localization results (GL) on μ CTs were then created by averaging GL_1 and GL_2 .

In addition to the GL created from the μ CT, the two experts also generated their best estimates of electrode locations on clinical CTs with the same iterative process. We denote the averaged estimates of expert YZ and RFL as IL_1 and IL_2 . Then, for each case, we average IL_1 and IL_2 to create the final image-based localization (IL) for the specific case, which we use to represent the overall best localization that is achievable manually when using the CT images. Next, the conventional and μ CT images were manually reoriented into a conventional orientation and then registered using standard rigid mutual information-based registration techniques.¹⁹ Because the anatomy is bony, a rigid registration has the degrees of freedom necessary to well align the two images. The registrations were visually inspected and confirmed to be accurate [see Figs. 2(a)–2(c)].

Upon visual inspection, we discovered that the CI electrode arrays had clearly moved between the conventional and the μ CTs in five cases out of the 35 specimens. The motion was obvious due to the large and coherent displacement vectors between the centroids of the electrodes in the registered conventional and μ CTs. An example case where motion occurred is shown in Fig. 2 and the displacement can be visualized in Figs. 2(d) and 2(e). As can be seen in Fig. 2(e), the left half of the array does not appear to have moved (no coherent displacements between the CT and μ CT electrodes in the isosurfaces); however, the right half of the array does appear to have moved between scans (coherent shifting to the right of all of the electrodes consistent with array bending). We hypothesize that this motion occurred because the cochlea was void of fluid that would typically stabilize the array and the array was not otherwise internally fixed in the specimens when being shipped from one imaging site to another between the time the conventional and μ CT scans were acquired. Because the array moved between scans, the μ CT no longer serves as an appropriate ground truth for the location of the electrode in the conventional scan for these cases. The remaining 30 cases had no obvious movement of the array between images, and we believe they still serve as a valid ground truth. Our final ground truth dataset consists of registered postimplantation conventional CT- μ CTs pairs and the GL and IL localization results of these 30 specimens.

2.2 Automatic Electrode Localization Method

Using our automated methods, the intracochlear anatomy was localized in the preimplantation CT,¹⁵ and the location of the electrodes relative to the anatomy was localized in the

postoperative CT after registration with the preoperative CT using an extension¹⁸ of a method developed by Noble et al.¹² Electrodes are localized by defining a point for each electrode that represents its centroid and then connecting all the electrodes from the basal to the apical direction in the correct order [shown in Fig. 1(d)]. The electrode localization procedure is summarized as follows: (1) the volume-of-interest (VOI), a $\sim 30 \times 30 \times 30$ mm³ bounding box around the cochlea, is identified via registration of the CT image with an atlas image. (2) A feature image is computed using the weighted sum of the intensity of the VOI and a blob filter response of the VOI. The blob filter is designed in a similar way as the Frangi vesselness filter²³ to enhance the spherical structures in the VOI. The feature image is thresholded to find regions-of-interest (ROIs) that contain electrodes. (3) Candidates-of-interest (COIs) are identified through a voxel thinning method²⁴ on the ROIs. The COIs represent potential electrode locations. (4) A graph-based path finding algorithm is used to identify the sequence of COIs that correspond to the electrodes in the electrode array. The algorithm relies on a cost function that includes appearance and shape-based terms to identify and correctly order the electrodes in the array. The appearance terms are designed to localize electrodes where there are bright, blob-like features in the image, and the shape-based terms are designed to localize the array of electrodes as a smooth curve with electrodes properly ordered and with spacing between electrodes that matches the *a priori* known electrode spacing. We refer to the resulting electrode localization as the automatic localization (AL).

2.3 Validation Approaches

To compare two given electrode localizations, we measure Euclidean distances between the corresponding electrode points [see Fig. 2(e)]. In our validation study, the difference between AL and GL represents the “overall” error of our automatic approach. The difference between GL and IL represents the error in localization due to errors inherent to the CT image, which we call the “image-based” error. The automatic electrode localization method being evaluated was designed to generate AL that approximates IL. Thus, the difference between AL and IL represents the error in localization due to the limitation of the algorithm, which we call the “algorithmic” error. However, the overall accuracy is a function of both algorithmic errors and errors inherent to the use of the CT image. Thus, to measure both types of errors independently, we also compare IL and GL to estimate image-based errors, and we compare AL and IL to measure algorithmic localization errors.

3 Results

3.1 Validation Study Results

Figure 3(a) shows boxplots of the mean, median, maximum, and the standard deviation of localization the errors between AL and GL across the 30 specimens in our dataset. In each boxplot, the median value is shown as a red line, 25th and 75th percentiles are indicated by the blue box, whiskers show the range of data points that fall within $1.5 \times$ the interquartile range from the 25th

Fig. 3 Boxplots of electrode localization errors between (a) AL-GL, (b) IL-GL, and (c) AL-IL.

Fig. 4 Comparison among electrode localization results generated by AL (automatic method in IGCIP), IL (image-based localization), and GL (ground truth localization we created in the study).

or 75th percentiles and are not considered outliers, and red crosses indicate the outlier data points. Comparing AL and GL, we found mean electrode localization errors of 0.13 mm and maximum localization error of 0.36 mm. Figure 3(b) shows similar boxplots of localization errors between IL and GL. The mean electrode localization error was 0.10 mm and the maximum localization error was 0.29 mm. Figure 3(c) shows boxplots of localization errors between AL and IL. The mean and maximum localization errors are 0.09 and 0.28 mm, respectively. This shows that our automatic method generates localization results that are close to the optimal localization results that can be generated by an expert from clinical postimplantation CTs. All localization errors are smaller than the length of one voxel diagonal of the conventional postimplantation CTs in our dataset. Figure 4 shows representative localization results generated by AL, IL, and GL for four cases (each specimen is implanted with a different type of electrode array). A paired t -test between the mean localization errors between AL-GL and AL-IL revealed a significant difference ($p < 10^{-8}$). This shows that the algorithmic errors that would be estimated if using the CT image to create a ground truth would be significantly different from the errors measured when using the μ CT to serve as ground truth. This result motivates the use of our high resolution ground truth dataset for rigorous evaluation of CI electrode localization methods. We also found AL-GL and IL-GL to be significantly different ($p < 10^{-6}$). However, the mean errors between AL-GL (0.13 mm) and IL-GL (0.10 mm) are very close and our AL method can generate results that are nearly as good as the most accurate localization results achievable by experts from clinical CTs.

3.2 Intra- and Interrater Variability of Expert Localizations

As can be seen from Fig. 5(a), to generate GL₁ and GL₂, both experts only need to generate two instances for all the 30 specimens. This indicates that intrarater repeatability is within 0.05 mm. This is expected because μ CTs have high resolution, which makes manual identification of the centroid of the electrodes easy. As can be seen from Fig. 5(b), on clinical CTs, more than two instances were required for seven cases which required three analyses and one case which required five analyses by one expert (RFL). This shows that on clinical CTs, intrarater repeatability errors are higher than for μ CTs. When comparing each individual manual localization performed on clinical CTs with the corresponding GL, we find both the experts have an average single manual localization error of 0.12 ± 0.05 mm. A two-tailed t -test between these errors and AL-GL errors (0.13 mm) found no statistically significant difference between the two ($p = 0.25$), which shows that errors in the AL are comparable to errors in an individual expert localization on the clinical CT.

Figures 6(a) and 6(b) show the boxplots of the mean, median, maximum, and the standard deviations of the interrater differences. From Fig. 6(a), we find the mean difference between GL₁ and GL₂ is 0.05 mm. This shows that interrater variability is low on μ CTs, especially when compared to the mean localization error we are measuring between AL and GL (0.13 mm). Thus, GL can be considered to be an accurate ground truth localization for rigorously characterizing the accuracy of our automatic electrode localization methods. This also suggests that one expert is adequate to perform ground truth generation on μ CTs since the interrater variability is considerably lower than the mean error of AL-GL (0.13 mm). From

Fig. 5 (a) and (b) The number of instances of manual localization results two experts need to generate on μ CTs and clinical CTs to reduce the intrarater error within 0.05 mm, respectively.

Fig. 6 Boxplots of interrater differences in the best estimates of electrode locations (a) on μ CTs (GL₁ versus GL₂) and (b) on clinical CTs (IL₁ versus IL₂).

Fig. 6(b), we find the mean difference between IL₁ and IL₂ is 0.08 mm. This value is still low but is slightly higher than the mean difference between GL₁ and GL₂ because clinical CTs have lower resolution. Because of that, experts have to use their judgement to estimate the position of the center of the contacts. The maximum difference between IL₁ and IL₂ (0.30 mm) is still lower than one voxel diagonal.

4 Conclusions

In this work, we create what is to the best of our knowledge the first high-resolution ground truth dataset for the validation of CI electrode localization methods. For all 30 cases in our dataset for which CI electrode array movement between conventional and μ CT imaging did not occur, our localization method was successful and highly accurate, with mean and maximum electrode localization errors of 0.13 and 0.36 mm. The mean and maximum image-based localization errors were 0.10 and 0.29 mm. Meanwhile, the mean and maximum localization errors between our automatic method and the results generated by experts on the clinical CT images were 0.09 and 0.28 mm. Altogether, these results show that our automatic CI electrode localization method achieves localization results that are close to the best possible localization that can be manually generated on the clinical CTs, and that errors due to the algorithm are typically smaller than errors due to the CT image quality. The sources of error inherent to the CT image include its limited resolution and the existence of image artifacts. The estimate of algorithmic error when using the CT image-based localization as the reference is significantly different than the estimation of the error when using the μ CT ground truth as the reference. While statistically significant, it should be noted that the difference between AL-GL (0.13 mm) and IL-GL (0.10 mm) is only 0.03 mm. With these values and AL-IL as small as 0.09 mm, we can conclude that our automatic method is nearly equivalent to the average of a number of meticulously performed expert localizations. Further, there is no statistical difference between our automatic results and an individual localization by an expert. Since individual localizations are currently standard practice with IGCIP, this suggests the automatic technique can replace manual localization without sacrificing performance. Nevertheless, the clinical significance for IGCIP of electrode localization errors needs to be investigated in future work.

We plan to do this by performing a prospective study where hearing performance differences are measured with CI recipients when using IGCIP plans that are created with different levels of electrode localization errors.

The ground truth dataset we have created in this study successfully permitted characterizing the accuracy of our method, which is critical to evaluate its performance for use in IGCIP and in evaluating the correlation between electrode position and hearing outcomes. In future work, we plan to use preimplantation μ CTs to define the ground truth position of intracochlear anatomy with high accuracy. This dataset can be used for evaluating the performance of the automatic intracochlear anatomy segmentation methods^{16,17} we have developed. With these highly accurate ground truth datasets, we can further study how electrode localization errors and anatomy segmentation errors impact IGCIP and our analysis of the correlation between electrode position and hearing outcomes.

Disclosures

No conflicts of interest, financial or otherwise, are declared by the authors.

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