Ocular Stethoscope: Auditory Support for Retinal Membrane Peeling

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Abstract. The peeling of an epiretinal membrane (ERM) is a complex procedure wherein a membrane, only a few micrometers thick, that develops on the retinal surface is delicately removed using microsurgical forceps. Insights regarding small gaps between the ERM and the retinal tissue are valuable for surgical decision-making, particularly in determining a suitable location to initiate the peeling. Depth-resolved imaging of the retina provided by intraoperative Optical Coherence Tomography (iOCT) enables visualization of this gap and supports decision-making. The common presentation of iOCT images during surgery in juxtaposition with the microscope view however requires surgeons to move their gaze from the surgical site, affecting proprioception and cognitive load. In this work, we introduce an alternative method utilizing auditory feedback as a sensory channel, designed to intuitively enhance the perception of ERM elevations. Our approach establishes an unsupervised innovative mapping between real-time OCT A-scans and the parameters of an acoustic model. This acoustic model conveys the physical characteristics of tissue structure through distinctive sound textures, at microtemporal resolution. Our experiments show that even subtle ERM elevations can be sonified. Expert clinician feedback confirms the impact of our method and an initial user study with 15 participants demonstrates the potential to perceive the gap between the ERM and the retinal tissue exclusively through auditory cues.

Keywords: Mixed Reality · Augmented Reality · Optical Coherence Tomography· Sonification · Auditory Feedback · Interaction Design
* contributed equally to this work.

1 Introduction

In retinal surgery, fine anatomical structures need to be manipulated with micron-level precision, while commonly an operating microscope provides primary visual access to the surgical site at the backside of the eye. An example of such a complex procedure is the peeling of an epiretinal membrane (ERM), an on average

$60\mu m$ thin membrane [30] that forms on top of the retina and, if left untreated, can lead to decreased central visual acuity [25]. Before peeling this membrane with a microsurgical forceps, typically, a synthetic dye is administered to the retina. This dye stains the inner limiting membrane (ILM) and enables the surgeon to visually distinguish the ERM located on top of it. A challenging, yet crucial aspect of the subsequent procedure is to identify a suitable region to grasp the membrane and initiate the peeling. While the ERM is typically attached to the retina, a gap as small as $45 \pm 8\ \mu m$ [20] between the ERM and the retina can occur, especially in patients where a large ERM stiffens and pulls the retina. In the medical community, different approaches have been proposed to perform ERM peeling [7]. Studies show that, on one hand, initiating the peeling in areas with higher ERM elevation can significantly reduce the number of required initial peeling grasps, thus reducing risks of retinal tissue damage, and improving surgery outcomes [20]. Other studies show that an elevated ERM can be an indicator for ERM re-occurences after surgery and thus propose to initiate the peeling at the borders of the ERM and perform ILM peeling in tandem with ERM peeling to reduce the risk of re-occurrences [25]. Regardless of the surgical approach, information regarding the existence and location of ERM elevations can govern the surgical approach and decision-making.

Precise visualization and quantification of subtle elevations in the ERM are in most cases not possible through the microscopic view, however, optical coherence tomography (OCT) has been shown to provide the required micron-level resolution [20]. Integrated with surgical microscopes, intraoperative OCT (iOCT) has shown benefits for surgical decision-making and surgery outcomes in ERM peeling procedures [8]. Yet, a fundamental question regarding the integration of iOCT together with surgical microscopes is to find adequate channels for the simultaneous presentation of multimodal information. In currently available systems, the microscopic view and iOCT images are typically presented in juxtaposition. Moving the gaze between different visual monitors during such delicate tasks however increases the cognitive load on surgeons and affects their proprioception, potentially interfering with the surgical flow and slowing down the procedure. Therefore, more advanced and intuitive ways of providing multimodal information without distracting the focus during critical surgical phases need to be developed.

An alternative way to convey auxiliary information is through distinctive sound features, generated from OCT imaging data. The human auditory system is highly skilled at discerning sonic qualities such as pitch, texture, timbre, and rhythm, efficiently capturing the dynamic characteristics of objects at micro-level temporal resolution. This ability enhances attention and enables quick comprehension of complex data, facilitating rapid environmental responses. In augmented reality (AR) and interaction design, incorporating sound was shown to enhance user experience, making interactions more engaging, dynamic, and immersive [31, 9]. Sonification is the systematic transformation of data into sound, aimed at enhancing communication and interpretation [13]. This approach has proven effective in a variety of applications, ranging from data exploration to

navigation [14]. However, integrating sonification into AR systems for highly sensitive and high-stakes tasks, such as ERM peeling, introduces significant challenges. Essential criteria for these models include their ability to process subtle dynamic changes in the imaged tissue structures and provide auditory feedback at micro-temporal resolution that is both accurate and intuitive to interpret, yet pleasant in a surgical context.

In this paper, we introduce a novel unsupervised method to generate auditory feedback representing the ERM and retinal structures. Our approach aims to enhance the perception of ERM elevations through distinctive sound features. Instead of defining a sonification model through explicit segmentations of OCT data, we propose a novel unsupervised mapping between OCT A-scans and an acoustic model, which robustly reacts to dynamic structural changes. Our experiments on various representative ERM cases show the generalizability of the method and demonstrate that even subtle ERM elevations can be distinctively conveyed through sound. Feedback from an expert clinician confirmed the impact of the method for ERM peeling and the results of an initial user study with 15 participants show that ERM elevations can be identified exclusively through auditory feedback. Diverging from conventional techniques of displaying OCT data, this approach could allow surgeons to focus visually on the microscope view while obtaining information exclusively present in OCT data via auditory feedback.

2 Related Work

Until now, only a few works have proposed specialized intraoperative systems to support retinal membrane peeling. To the best of our knowledge, these have been limited to visualizing an already peeled ERM [29] and improved instrument navigation towards a selected cross-section at the peeling target [26] in 3D OCT renderings. Sonification has been introduced to the medical field, offering a wide range of applications [2, 12, 17, 23], particularly demonstrating potential in areas such as image-guided surgery [3], where it serves as an auxiliary aid to a visualization setup. Often, mapping functions are employed that directly convert input data features into the global sound parameters of a synthesizer such as pitch, amplitude, and timbre. Such techniques have been widely used to sonify the position or status of surgical instruments relative to predetermined structures [12, 33, 19, 32, 24], or to translate explicitly defined low-dimensional features of medical imaging data into acoustic features [2, 23].

Navigating complex scenarios, such as interpreting detailed anatomical structures via auditory means, requires an intricate method to process multidimensional data efficiently. Model-based sonification (MBS) offers a promising approach by integrating unsupervised data attributes with the elements of a sound model, thus facilitating an interactive and tangible exploration of the data [15]. The development of the sound model is usually achieved through physical modeling synthesis [6]. This method aims to replicate the physical properties of real-world instruments, thereby simulating the behavior of tangible objects. It

allows for modal analysis, a process that identifies the system's dynamic characteristics, such as natural frequencies, damping factors, and mode shapes. The outcome of this analysis is a synthesis approach grounded in physical principles, known as modal synthesis [1]. In [18], MBS was employed to create a tissue-informed sound model capable of producing distinguishable sounds that reflect anatomical tissue characteristics. The practicality and efficiency of this model in scenarios requiring real-time feedback with high temporal resolution and micron-level interactions are yet to be investigated.
A significant number of sonification methods applied in the medical field, particularly for navigation [3, 33, 32] and medical imaging [2, 23, 11], adopt a purely technical approach to map data to sound in an abstract manner. These methods directly map certain measurements to acoustic parameters such as pitch or amplitude, using sound and frequency as abstract representations of numerical values. However, these representations lack a connection to the actual physics, such as tissue characteristics. This lack of connection makes it difficult to comprehend these methods, leading to increased mental load and an extended learning period. Conversely, research in neuroscience has systematically demonstrated that the human brain is particularly well-suited to processing natural sounds that are behaviorally relevant [27]. Moreover, most of these techniques depend on the use of supervised data, requiring prior semantic knowledge of the data. This however limits the adaptability and scalability of these methods for unseen examples. Furthermore, the current state of the art [18] lacks methods that effectively communicate high-level structural information through auditory channels with micro-temporal precision. Utilizing the general framework outlined in [18], we aim to sonify subtle structural patterns in OCT data to support ERM peeling, underscoring the unique contributions of our proposed approach.

3 Method

We propose a novel method to transform structural patterns of the ERM and the retinal tissue into discernible auditory textures. The proposed method takes an OCT A-scan as input, computes a local A-scan attenuation map, and assigns a region of interest (RoI) within the generated data to an acoustic model capable of producing sound grains. A sequence of retina-informed sound signals is achieved by the concatenation of sound grains generated from individual excitations of the acoustic model.

3.1 Local Attenuation Map

We apply minimal processing on each OCT A-scan to amplify small structures, such as the ERM, and improve their differentiation from the background. For this purpose, we introduce a local attenuation map, which is derived from [28] and computes the optical attenuation within a small local window below a specific A-scan index. For a specific depth index i along the A-scan, we compute the

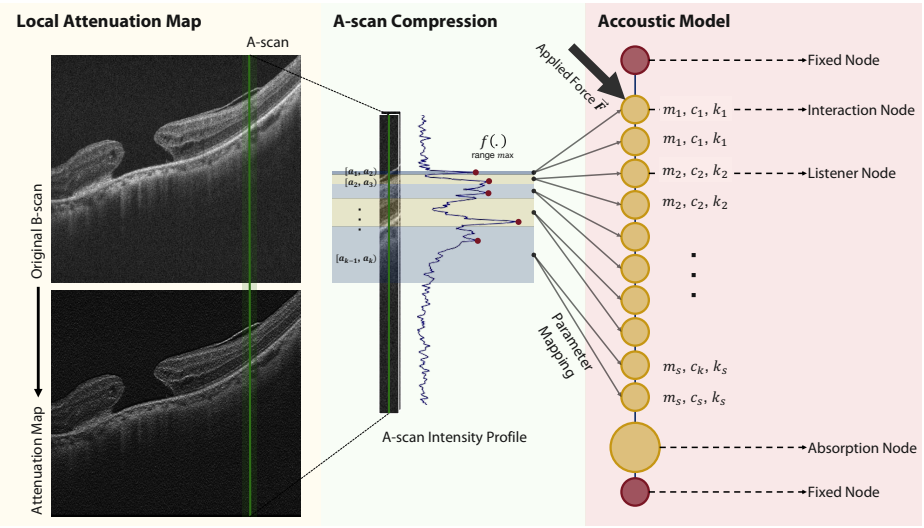

Fig. 1: Overview of the proposed method: For each A-scan, we generate a local attenuation map. The A-scan ROI and its local attenuation map are compressed, and the parameters of the acoustic model are calculated.

local attenuation $\mu(i)$ as:

$$\mu(i) = \frac{I(i)}{2\Delta \sum_{j=i+1}^{i+w} I(j)} \tag{1}$$

where $I(i)$ is the A-scan intensity at index i, w is the local window size, and Δ is the axial pixel resolution in mm. During our experiments, we empirically chose a window size $w = 5$. A comparison of an OCT B-scan with the resulting local attenuation map generated from the individual A-scans is shown on the left side in Fig. 1. The generation of this map leads to more distinctive sound textures when forwarded to the acoustic model described in Sec. 3.3.

3.2 A-scan Compression

The required resolution for sonification is not uniformly distributed along an A-scan. A large part of the A-scan represents the vitreous chamber above the retina, which we exclude by applying simple processing as presented in [22]. Thus, we start A-scan compression with the first occurrence of a distinctive structure. This area has a great significance as it includes the gaps formed by an elevated ERM, if such gaps happen to exist. However, the retinal structures between the ILM and RPE (retinal pigment epithelium), or below the RPE, have less impact on our application. Therefore, it is sensible to intelligently group the retina into several intervals. Defining s intervals $[a_1, a_2), [a_2, a_3), ..., [a_{s-1}, a_s)$ for an A-scan I, together with a function $f : \mathbb{R}^n \rightarrow \mathbb{R}$ applied to each interval,

reduces I into $\mathbf{p} \in \mathbb{R}^s$, where $\mathbf{p}_i := f(I_{a_{i-1}:a_i})$ (Fig. 1). As the function f needs to be sensitive to the values in the provided range, we chose f to be the max function, in contrast to average which is less sensitive to sudden changes in a range. At the same time, the intervals guarantee a higher resolution on topmost areas if $|a_{i-1} - a_i| < |a_{j-1} - a_j| \iff i < j$ is satisfied. While in theory there are unlimited possibilities to choose such intervals (e.g. exponential series), we chose the well-known Fibonacci sequence, which emphasizes single intensities at the surface and groups intensities below.

3.3 Acoustic Model for Sonification of OCT A-scans

A physically relevant representation of objects' acoustics requires considering both spectral and temporal features. As data dimensionality increases, managing these features and their mappings becomes more challenging, necessitating case-specific designs. Physical modeling efficiently handles these mappings by incorporating the spatial characteristics of the imaging data and optimizes the process with a minimal number of parameters. We employed a physical modeling approach to create the acoustic model, which operates on the principles of a damped harmonic oscillator, simulating the behavior of oscillatory systems by considering energy loss due to friction or other impeding forces. A damped harmonic oscillator consists of an oscillating node, a fixed node, and a damped spring connecting these two nodes. The equilibrium state of the system considering any external forces exerted on the model is represented as

$$\vec{F}(t) = m\ddot{x} + c\dot{x} + kx \tag{2}$$

where m denotes mass, $\ddot{x}$ the acceleration of the object, c the damping coefficient, $\dot{x}$ is the velocity of the object, k the stiffness of the system, and x the displacement of the object from its equilibrium position, and $\vec{F}(t)$ represents the external force as a function of time.

The model parameters m, c, and k influence the model's resonant properties according to $\vec{F}$, determining sound temporal features such as attack and decay time and sustain level across the frequency spectrum. These factors contribute to producing a natural sound that is relevant to the tissue characteristics. To maintain the spatial coherence of the compressed A-scan data, as described in Sec. 3.2, we extended the damped harmonic oscillator model. This extension includes connecting additional nodes with damped springs of uniform length, constructing a string-shaped model. The entire setup is anchored by two fixed nodes at each end, which have zero displacements, as shown in Fig. 1. The model features $n \times s$ nodes, which represent each of the s A-scan data segments with n number of nodes. In this work, we set n to 2 and s to 8, to achieve an optimised performance and sufficient resolution. By applying a force $\vec{F}$ to one of the nodes, the force is propagated throughout the model, with the resultant audio signal being captured by one or several nodes. The values of the intervals are mapped to m, c, and k through a transfer function.

Eq. 2 serves as the foundation for computing the displacements of nodes. Through

accurate modeling of how these nodes respond to external forces and their inherent physical constraints, we simulate the vibrations that generate sound waves. The implementation of this model was carried out using miPhysics[4].

Model Configuration When applying this model to an application demanding rapid response times, two primary challenges arise that require simultaneous consideration: maintaining the model's stability and ensuring distinct sound clarity for an effective differentiation between signal states. In this context, stability denotes the necessity for the model to rapidly damp the propagation of force, aiming to mitigate the following issues: firstly, the overlap with subsequent excitations, and secondly, accumulation and amplification as the force traverses through the model, potentially overwhelming the model with energy and causing failure. To achieve this, we applied high damping to the nodes. However, excessive damping will lead to the second issue, reducing the sound clarity. Accordingly, we modified the string model by adding an extra node at the bottom part of the model, with a significantly increased damping parameter. This adjustment helps absorb vibrations to a certain extent while allowing the other nodes to oscillate more freely. This contributes to a clearer contrast in the resulting sound while also reducing noise and ensuring the stability of the model. We set the uppermost node to receive the input force, which symbolizes an imaginary surgical tool interacting and applying forces to the retina surface. Moreover, we select two nodes from the second and third intervals for signal extraction, prioritizing the model's upper regions, to listen particularly to potential gaps between ERM and retina. Modifying the positions of these nodes significantly affects the resultant sound, potentially leading to confusion if not selected carefully. The setup of the mapping functions which translate the input data into the model parameters m, c, and k, is based on their influence on the sound to accurately represent tissue characteristics. Input data with higher values are mapped to increased mass and damping, while lower values correspond to decreased mass and damping. Conversely, higher intensity values are mapped to lower stiffness, and lower intensity values correspond to higher stiffness. The transfer functions f_m, f_c, and f_k map image intensity I within the normalized range $[0.001, 1]$ to the model parameters m (kg), c (N.s/m), and k (N/m), respectively. These mappings are empirically determined to optimize the trade-off between high sound contrast and model stability.

4 Experiments and Results

Demonstration of Representative ERM Cases To show the generalizability of the proposed method to various ERM cases, we demonstrate spectrograms of representative B-scans from the publicly available dataset presented in [10]. The spectrograms depicted in Fig. 2 illustrate the ability to distinguish between

[4] https://github.com/mi-creative/miPhysics_Processing

regions featuring elevated ERM and those with an attached membrane. Furthermore, this differentiation persists even in scenarios where the ERM is only marginally elevated and minor gaps are visible in the B-scan. We refer the reader to our supplementary material for audio examples with distinctive sounds.

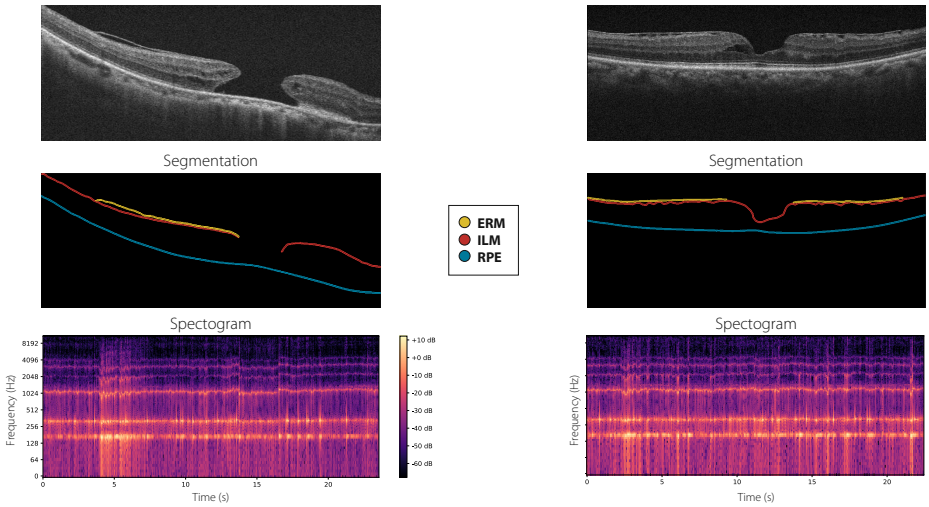

Fig. 2: Visualization of the spectrogram of two diagnostic OCT scans. We refer to our supplementary material to access the corresponding audio files.

User Study To evaluate the efficacy of the method in conveying structural information, we conducted a user study involving 15 novice participants. The users were introduced to the concept by demonstrating the sonification of a simulated B-scan, produced using an existing simulation surgical simulation system[5]. Following a brief training session, participants were asked to identify the presence and locations of ERM elevations within 10 randomly ordered B-scans, which contained zero, one, or two gaps. Among 150 trials, in 94% of the cases, a correct number of gaps were predicted. The distance error of the selected area, from the total 208 number of gaps, was 12.89 ± 15.09 pixels, 98.5% being within the area of the elevated ERM.

Expert Feedback We finally conducted an interview and an explorative user study with an ophthalmic expert to evaluate the potential of the method. First, sonification of a diagnostic OCT B-scan was presented, for which the expert was able to easily associate acoustic feedback with elevations in ERM. Overall, the clinician found the method to be very effective, as even slight ERM elevations

[5] www.syntheseyes.de

could be sonified. Furthermore, we presented a potential user interface in a simulated surgical scenario with integrated ERM, where a forceps was moved across the retina and a simulated OCT A-scan in between the forceps tips was sonified. Qualitative feedback included that such a system could assist surgeons in identifying starting points for grasping, particularly in cases where the ERM covers a larger area of the retina. In addition, the expert suggested that the method could reduce the amount of administered synthetic dye, which was associated with a toxic effect on retinal cells [21].

5 Discussion and Conclusion

As the proposed method involves a generalizable unsupervised sonification approach, it is not only limited to conveying ERM elevations but could be applied in a broader range of ophthalmic scenarios. The unsupervised nature of this approach, which does not require explicit segmentations of fine tissue structures, seems to be especially useful in cases where segmentation is not feasible due to the high processing requirements of real-time data acquisition rates. Immediate extensions could be to also sonify the peeling procedure or any structural changes during macular hole surgery. For integration into a surgical system, we envision that our system could be employed with recent 4D iOCT systems [4] that enable continuous scanning of the surgical site. In such a scenario, similar to the simulation environment in our explorative study, existing methods [16] could be used to track the surgical instrument and as an input device to select the sonified A-scan. Alternatively, our proposed method could be employed with OCT A-scan integrated instruments [5]. In conclusion, we proposed a novel concept to sonify gaps between an elevated ERM and retinal structure. Spectrograms, as well as our user study, showed that relevant structural patterns could easily be differentiated through auditory feedback. Clinician feedback confirmed the impact of this method for retinal membrane surgery and the presence of distinctive sound textures to identify even slight elevations of the ERM. Further development of such methods could reduce the amount of synthetic dye and improve decision-making and surgery outcomes.

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