

**Image Reconstruction for Fiber Bundle Endomicroscopy Using Cubic Spline Interpolation**

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Structured Abstract

The goal of the project is to improve image processing techniques used in fiber beam endoscopes (FBE). While FBE can provide real-time microscopic views of living tissue, it also has some limitations, such as low image resolution, artifacts such as honeycomb effects, and complex post-processing requirements. These issues make it difficult to diagnose images in a clinical setting. The project enhances endoscopic image processing techniques through SciPy and OpenCV. The aim is to develop and implement new image processing algorithms to effectively eliminate artifacts and improve image resolution.

This project uses various techniques in SciPy, including B-spline interpolation, cubic spline interpolation, etc. to create a custom spline interpolation scheme to solve the core artifacts in the image. This method combines multiple image processing techniques to improve image resolution while maintaining system efficiency.

DECLARATION

文本

AI 生成的内容可能不正确。I, Shao Jiahui, student of the School of Science and Engineering at the University of Dundee, hereby declare that I am the sole author of this thesis titled ‘Image Reconstruction for Fiber Bundle Endomicroscopy Using Cubic Spline Interpolation’. All work, unless otherwise specified, is my own and has not been previously accepted for a higher degree.

Signed: Date:20/4/2025

(Shao Jiahui)

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2. Introduction

Endomicroscopy is a relatively advanced medical imaging technology, which combines traditional Endomicroscopy with microscopic imaging (Perperidis et al., 2020). Unlike traditional biopsy techniques, which require tissue samples to be taken for analysis, Endomicroscopy can perform an 'optical biopsy' while inflicting damage on troops' bodies. This provides an efficient and non-invasive solution for early disease detection and diagnosis.

Despite its many advantages, fiber beam endoscopes have some problems. The main problem is the inherent limitations of the fiber bundle itself, which can lead to reduced image resolution, image distortion due to core artifacts (often referred to as the "honeycomb effect"), and the impact of background noise (Perperidis et al., 2020). These problems not only reduce the image quality, but also make the analysis and diagnosis of the image more complicated, thus reducing the readability of the image.

Improving the image quality of fiber beam endoscopes can improve their diagnostic accuracy and practicability in clinical Settings. By reducing artifacts and improving resolution, healthcare professionals can more clearly identify and evaluate organizational structure (Perperidis et al., 2020). This can not only improve the accuracy of disease detection, but also help doctors perform minimally invasive surgery more accurately, provide better treatment results for patients and reduce the probability of complications.

The project aims to address these shortcomings by improving the image processing technology used in fiber beam endoscopes. The project will use Python and OpenCV to develop new algorithms that reduce cellular effects and improve image resolution. Custom filters are created using methods such as convolutional filtering, edge detection and Fourier transform, and will be combined with various image processing methods to improve the resolution and overall quality of the image, while ensuring the efficiency of real-time applications.

The following is a brief introduction to the article structure of the project, which is divided into seven chapters:

**Chapter 1: Introduction**

This chapter will summarize the importance of Fiber-Bundle Endomicroscopy (FBE) and its application in medicine, and briefly discuss its advantages in real-time high-resolution imaging and optical biopsy. At the same time, this chapter will point out the main problems existing in current fiber beam endoscopes, including low resolution, core pattern artifacts (such as honeycomb effect) and other problems. This chapter will also clarify the research goal of this paper, which is to develop new image processing algorithms using SciPy and OpenCV to solve these problems.

**Chapter 2: Background**

This chapter will delve into how fiber beam endoscopes work, including how fiber bundles transmit images and the causes of artifacts. At the same time, I will review how existing image processing methods solve the problem of artifacts and insufficient resolution, and discuss the limitations of these methods. Finally, this chapter will introduce the advantages of SciPy and OpenCV in image processing, as well as their potential for real-time applications.

**Chapter 3: Materials and Methods**

This chapter will describe the tools used in the study in detail and introduce the image processing algorithms developed based on SciPy and OpenCV. This chapter will introduce the basic principles of spline interpolation to remove cell artifacts and improve image resolution. In addition, this chapter will introduce the implementation details of the algorithm, parameter settings, and image quality assessment methods.

**Chapter 4: Results**

This chapter presents the image results of the fiber bundle endoscope after processing with the new algorithm. By comparing with the original image, the artifact removal effect and the degree of resolution improvement will be shown. At the same time, this chapter will provide image quality evaluation indicators to evaluate the performance of the algorithm.

**Chapter 5: Discussion**

In this chapter, the advantages and disadvantages of the new algorithm in fiber beam endomicroscopy image processing will be discussed based on the results of image processing. The potential value of removing artifacts and improving resolution in clinical applications is also discussed, as well as the technical challenges faced in real-time processing. At the same time, this chapter will compare the performance differences between the methods used in this project and existing methods, and analyze the possible factors that affect the results.

**Chapter 6: Conclusion and Future Work**

This chapter will summarize the main research results of the project, indicate the potential contribution of the research to medical imaging technology, and summarize breakthroughs in solving low resolution and artifact problems. It also proposes possible research directions in the future, and provides clear directions for follow-up research by looking forward to future improvements and challenges.

1. Background
   1. The Development of Endoscopes
      1. The early development of medical imaging

The history of the light microscope began with the use of lenses. The word "Lens" is derived from the word "lentil" (common name: flat beans, scientific name: Lens Culinaris)(ARAKI, 2017). In ancient times, the Greeks called the convex lens a concentrating tool, and the lens was used to focus sunlight on the parchment to punch holes, burn wounds, and so on. It was later converted into a simple magnifying glass in the 11th century. These early lenses, made of quartz and glass, allowed scholars and craftsmen to see the world more closely, laying the foundation for later scientific exploration. At the end of the 16th century, the Dutch optician Hans Janssen and his son Zacharias Janssen invented the first two-lens microscope, as shown in Fig. 1(ARAKI, 2017). This pioneering device uses objectives and eyepieces to greatly increase magnification. Although rudimentary by today's standards, the invention revealed details previously invisible to the naked eye and marked the beginning of a transformative journey for scientific instrumentation.

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Fig. 1 Microscope depicted in the Micrographic (1665) by Robert Hooke.

In 1665, Robert Hooke's groundbreaking observations brought the microscope into the spotlight. Hooke used an elaborate two-lens microscope to look at the small compartments in the cork and called them "cells." His work “Micrograph” not only revealed the hidden structures of nature, but also captured the imagination of the public (ARAKI, 2017). However, due to the severe distortion of the observed images, the upper limit of magnification is about 150 times, which hinders the widespread application of the microscope. Around the same time, Dutch businessman Antoni van Leeuwenhoek invented a single-lens microscope, shown in Fig. 2(ARAKI, 2017). His single-lens microscope was simpler but more accurate, with higher clarity and magnification of over 200 times.

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Fig. 2 Leeuwenhoek’s microscope.

In the 19th century, as technology continued to advance, Carl Zeiss and his collaborators Ernst Abbe and Otto Schott improved the microscope's composite lens and made a high-performance stand-type microscope in 1857, shown in Fig. 3(ARAKI, 2017). In order to solve the chromatic aberration problem that existed in earlier designs, Abbe established a theoretical framework that linked spatial resolution to the wavelength of light, and designed " Apochromat" that were capable of presenting highly detailed and accurate images and pushing the spatial resolution to the physical limit of 0.2 microns of visible light (ARAKI, 2017). These improvements transformed the microscope from a simple magnifying tool to a precision instrument at the heart of scientific discovery.

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Fig. 3 First stand-type microscope produced in the Zeiss workshop. The photograph was made available by the Zeiss Archives, Germany.

Despite the new achievement, the volatility of light causes diffraction, which creates a circle around the blurred image. In order to solve this problem, Marvin Minsky proposed the confocal imaging principle in the middle of the 20th century (ARAKI, 2017). By selectively irradiating and detecting light from the plane of focus, confocal microscopy eliminates out-of-focus blurring, resulting in sharper images and better depth resolution, as shown in Figure 4(ARAKI, 2017). Laser scanning confocal microscopy is the most widely used confocal variant today and has contributed greatly to scientific and industrial fields such as life sciences, materials science, and semiconductor inspection.

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Fig. 4 Configuration of the confocal microscope optics.

* + 1. The advent of endoscopy

To look inside the body without causing harm. Philipp Bozzini published the "Lichtleiter" in 1807. Bozzini's device uses candles and mirrors to direct light into the human body, allowing for basic interior visualization (Reuter, 2000). Although the device is still rudimentary, it represents a new way of thinking about using light to explore the inaccessible anatomy of the human body. Despite resistance from contemporaries, this innovative move set the stage for future advances in medical imaging

In the 19th century, technological developments further refined Bozzini's original vision. By the 1850s, Antoine Jean Desormeaux, known as the "father of the endoscope," had improved the Lichtleiter (Reuter, 2000). He combined lights fueled by alcohol and turpentine for better lighting. His improvements enabled doctors to perform more detailed examinations of the urinary tract and bladder, marking the first practical application of endoscopic technology. However, limited by poor light and lack of flexibility, these instruments are bulky and risky to use.

The advent of electric light in the late 19th century revolutionized endoscopy (Reuter, 2000). With the invention of the incandescent light bulb by Thomas Edison, small light sources can now be integrated directly into endoscopic instruments. This innovation greatly improves visibility and opens up new possibilities for internal inspection. By the early 20th century, Hans Christian Jacobaeus applied an endoscope to the chest cavity and performed the first thoracoscopic examination.

A key breakthrough in endoscopic technology came in the 1950s with the introduction of optical fiber. Harold Hopkins proposed the use of flexible glass fibers to transmit light and images. Hopkins' rod lens system further improves clarity by minimizing light loss and distortion (Reuter, 2000). During the same period, the development of gastroscopes allowed doctors to observe the gastrointestinal tract in unprecedented detail and in a safe manner. These improvements not only improve image quality, but also provide greater flexibility and operability.

With the maturity of endoscope technology, its application scope has expanded rapidly. By the end of the 20th century, endoscopy was no longer limited to diagnostic procedures, but became an important tool for minimally invasive surgery (Reuter, 2000). Instruments such as laparoscopy and arthroscopy allow surgeons to perform complex surgeries through small incisions, reducing patient recovery time and minimizing complications. In addition, video endoscopy, introduced in the 1980s, replaced the traditional eyepiece system with a camera, allowing real-time image visualization on a monitor (Doi, 2006).

* 1. Development of Fibre-Bundle Endomicroscopy
     1. The emergence of optical fiber imaging technology

The introduction of optical fiber bundles has revolutionized medical imaging technology, providing new solutions for capturing high-resolution images (Zhou & Jokerst, 2020). These fiber bundles consist of tens of thousands of fiber cores whose relative positions remain constant along the length of the bundle. This "coherent" arrangement of the fiber core distinguishes the imaging beam from the "incoherent" beam, which can only be used for illumination. Even in complex environments, the fiber bundle maintains the relative position of the fiber core, enabling detailed image reconstruction.

Since the 1950s, fiber endoscopy (flexible medical endoscopy) has relied on fiber optic imaging bundles, initially using eyepieces to allow the operator to look directly at the transmitted image, and later evolving to a camera built into the endoscope handle for enhanced imaging capabilities (Zhou & Jokerst, 2020). Even after the advent of high-quality cutting-edge chip cameras, fiber bundles are still widely used in ultra-thin endoscopes and endoscopic microscopes.

There are two main types of fiber bundles used for imaging: fused and leached (Vyas et al., 2018). Fused fiber bundles: The fiber core is embedded in the shared cladding to enhance structural stability. Leached fiber bundles: Provide greater flexibility by removing the spacer material between the fibers, are suitable for navigating complex biological structures, have a much smaller bending radius than fused fiber bundles, but typically have a lower core density (Vyas et al., 2018). Both types of fiber bundles can be made small enough and flexible enough to allow them to be widely used in medicine.

In the 1950s and 1960s, fiber bundles were integrated into medical imaging systems. Improvements in optical fiber manufacturing processes and innovations in cladding materials have increased the efficiency and durability of light transmission, paving the way for the widespread use of optical fiber bundles in diagnostic and therapeutic processes (Vyas et al., 2018).

The performance of fiber bundles has improved significantly with the advancement of multi-mode fiber (MMF) and single-mode fiber (SMF) technologies: Multi-mode fiber (MMF) : supports higher light energy transmission and is suitable for deep tissue imaging (Zhou & Jokerst, 2020). Single-mode fiber (SMF) : Enhanced imaging resolution through precise optical focusing for fine imaging needs such as fluorescence microscopy (Zhou & Jokerst, 2020). These fiber optic technologies have laid the foundation for the development of multimodal imaging systems such as photoacoustic imaging (PAI), optical coherence tomography (OCT), and confocal fluorescence microscopy. In addition, the shift from mechanical scanning to optical transmission has further driven advances in fiber optic imaging. For example, the application of graded refractive index lenses and micromirrors has improved the performance of optical systems while laying the foundation for the development of ultra-thin endoscopes.

In recent years, the innovation of optical fiber technology has been endless, and the development of ultra-optics has contributed to the birth of meta-optic fiber endoscopes (MOFIE) (Fröch et al., 2023). It integrates the meta surface at the far end of the probe, enabling real-time full-color imaging while reducing the rigid tip length, providing greater flexibility and miniaturization for minimally invasive surgery and high-resolution tissue analysis (Fröch et al., 2023).

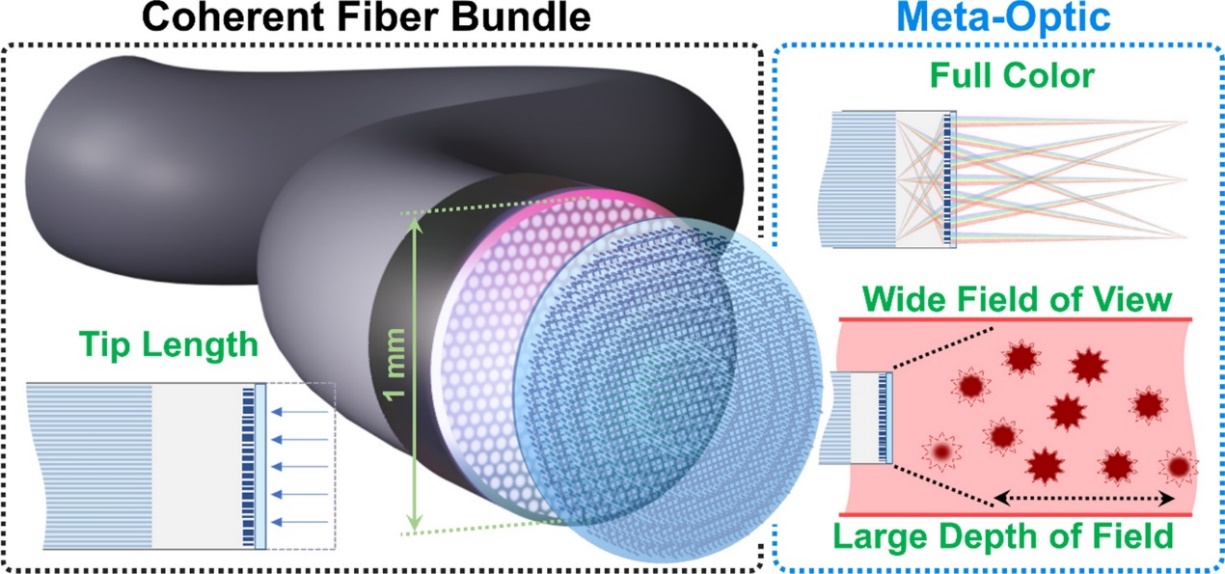


Fig. 5 Schematic of the meta-optical fiber endoscope

* + 1. Endomicroscopy concept and early implementation

The integration of microscope and endoscope marks a new leap forward in the field of medical imaging, which combines high-resolution optical visualization with the minimally invasive benefits of endoscopic technology. In the mid-20th century, the medical community desperately needed a tool that could image at the cellular level of living tissue, especially for areas that were difficult to reach with traditional microscopes.

The concept of endomicroscopy originated from the idea of observing histological and pathological changes on a microscopic scale in vivo, while avoiding invasive biopsies. The initial realization of this concept has benefited from significant advances in optical fiber technology. The precise arrangement of the fibers in the fiber bundle allows light and image data to be transmitted through a flexible and delicate probe that can travel through the complex internal structure of the human body (Perperidis et al., 2020).

At first, these devices mainly relied on simple lighting systems and direct observation through eyepieces, thus providing relatively limited magnification and resolution. However, the rise of fluorescence imaging in the 1980s brought a major breakthrough in this field. Fluorescence imaging techniques allow these fine structures to stand out by enhancing the contrast of cellular and subcellular structures. Subsequently, confocal microscopy, an important innovation, was successfully miniaturized and applied to endoscopic probes, enabling optical slicing and depth resolution imaging.

* 1. Compare With Other Devices
     1. Wide-Field endoscope

Wide-Field endoscope is a medical device that uses a wide-Field lens and advanced optical system to examine organs and tissues in the body, and is widely used in medical diagnosis, especially in gastroenterology (Luo et al., 2021). It uses a camera at the far end of the endoscope to provide a large field of view, allowing clinicians to see the entire organ surface in real time. The images are usually illuminated by white light and equipped with a high-resolution camera system to ensure that the images are clear and rich in detail (Luo et al., 2021). And the endoscope is exquisitely designed, easy to bend and turn in the body, suitable for complex anatomical areas.

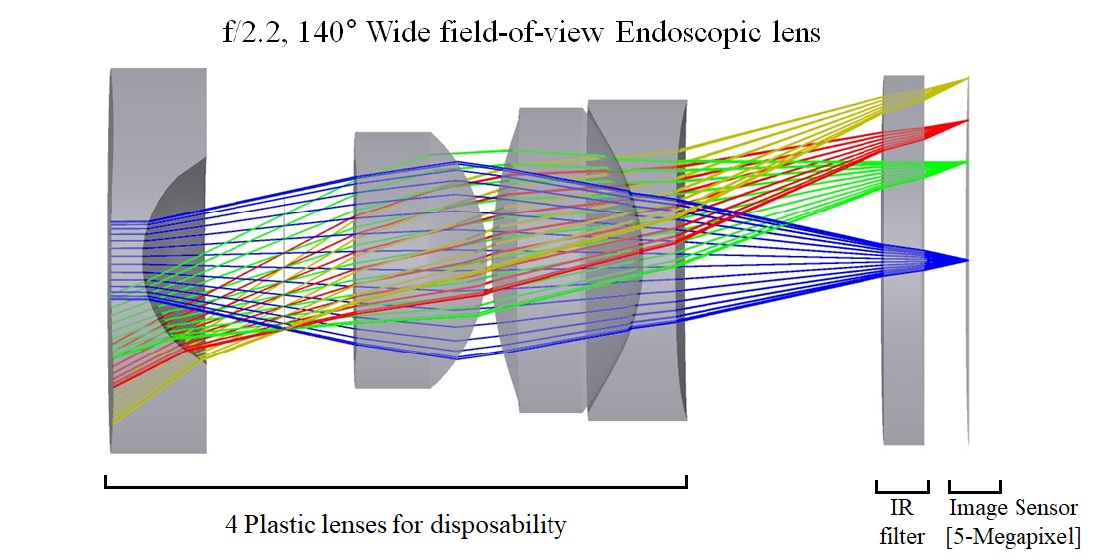


Fig. 6 Schematic diagram of Wide-Field endoscope

The advantage of wide-Field endoscopes is that they are good at detecting macroscopic lesions, ulcers and structural abnormalities. Its wide field of view, combined with high-definition images, helps in the early detection of small lesions and improves diagnostic accuracy (Luo et al., 2021). Such as colonoscopy and upper gastrointestinal evaluation. And because of the wide coverage, doctors can complete the examination in a relatively short time, improving medical efficiency.

However, wide-Field endoscopes cannot distinguish cellular or subcellular details due to firmware limitations. Subtle lesions, such as early stage cancer or dysplasia, often require a biopsy to confirm the condition because of the lower resolution and contrast of wide-Field imaging (Luo et al., 2021). In addition, because the white light used by wide-Field endoscopes limits their ability to distinguish between tissue types or identify specific molecular markers, it reduces their sensitivity to detect early or small-scale diseases.

* + 1. Confocal laser microendoscopy (CLE)

Confocal laser endomicroscopy is an advanced imaging method that combines confocal microscopy technology and endoscope, which can achieve high resolution imaging at the cell level in vivo, and is known as the "optical biopsy" technology (Chauhan et al., 2014). CLE uses a low-power laser as a light source and subsequently detects the fluorescence of the light reflected from the tissue through the pinholes (Neumann et al., 2010). Only the return light that is refocused through the pinhole is detected. Light that is reflected and scattered from illuminated objects at other geometric angles or that is refocused outside the pinhole plane will be excluded from detection (Chauhan et al., 2014). Therefore, CLE provides high-resolution images for optical biopsy and in vivo histological examination. There are two main types of CLE: endoscope-based (eCLE) and probe-based (pCLE) (Neumann et al., 2010). eCLE integrates confocal scanners into the tip of the endoscope, while pCLE relies on fiber beam technology for light transmission and collection.

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Fig. 7 Schematic of confocal laser endomicroscopy principles

The advantage of CLE is that real-time histological imaging can be performed, allowing clinicians to distinguish between benign and malignant tissue without performing a traditional biopsy (Chauhan et al., 2014). Its high resolution and contrast make it ideal for oncology applications, especially in detecting early cancer and assessing tissue margins during surgery.

The drawback of CLE is that the field of view is significantly smaller than that of a wide-Field endoscope, which limits its application in a wide range of investigations (Chauhan et al., 2014). In addition, due to its reliance on fluorescence imaging, additional exogenous contrast agents need to be added, which may increase the complexity of the procedure and potential side effects (Chauhan et al., 2014). In addition to this, CLE systems are much more expensive and their maintenance costs are much higher, which makes them not a good choice for regular diagnostics (Neumann et al., 2010).

* + 1. Optical coherence tomography

Optical coherence Tomography (OCT) is a non-invasive imaging technique that provides high-resolution cross-sectional views of tissue microstructure. It uses low coherence interferometry to measure backscattered light from different tissue depths to create detailed volumetric images. The axial resolution of OCT can reach a few micrometers, comparable to histology, and its depth of penetration ranges from 1 to 3mm, depending on the wavelength used.

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Fig. 8 Low-coherence tomography with a sample containing structures at different depths

The strength of OCT is its excellent performance in structural imaging, which is particularly useful in ophthalmology, cardiology, and gastroenterology. Its noninvasive ability to image the submucosa can detect subtle changes in tissue structure, such as early tumor transformation. Unlike CLE, OCT does not require contrast media to generate images in real time, making it suitable for longitudinal monitoring.

While OCT has excellent depth resolution, its lateral resolution is generally not as good as CLE's, which limits its application in cell-level imaging. In addition, OCT lacks the molecular contrast provided by fluorescence technology, limiting its ability to distinguish tissue types based on biochemical markers. Its high cost and specialized training requirements have also become a major obstacle to its widespread use.

* + 1. Comparison with fiber bundle endoscopy

Each technology has its own unique advantages. Unlike wide-Field endoscopes, FBE can provide cellular level detail, but its field of view is smaller and cannot replace wide-Field endoscopes for large-scale screening. Compared to CLE, FBE is more versatile and its systems are simpler and less costly, especially for ultra-thin probes used in confined Spaces (Rasmussen et al., 2015). Finally, while OCT excels at deep resolution imaging, FBE offers higher lateral resolution and is suitable for cell-level diagnosis, which is critical for the diagnosis and treatment of certain diseases.

* 1. Limitations of FBE
     1. Inherent limitation

The most visually striking and limiting artifact of an imaging scene when transmitted through a coherent fiber bundle is the so-called cellular effect. The reason for this artifact is that each fiber core acts as an independent channel of light, while the cladding between the fibers does not transmit image information. This creates patterned artifacts similar to honeycombs in the reconstructed images, greatly reducing the image quality. Images are sampled at discrete points (cores) rather than continuously. Each core represents a separate part of the scene, but the spacing between cores leaves gaps in the sampling. In addition, due to manufacturing inconsistencies, individual cores within the fiber bundles often exhibit changes in the efficiency of light transmission. This variability results in uneven lighting, which complicates an accurate representation of organizational structure. The self-fluorescence emitted by the fiber itself, especially at ordinary excitation wavelengths such as 488nm, adds noise to the signal, further reducing the signal-to-noise ratio and contrast of the image.

These limitations can have an impact on imaging. Discrete sampling results in reduced spatial resolution, which affects the evaluation of the image. The change of optical coupling between cores will cause the brightness of the entire image to be inconsistent. The honeycomb pattern can mask the subtle pathological features and affect the accuracy of diagnosis. Therefore, complex reconstruction algorithms are needed to suppress the cellular effect and improve the resolution.

* + 1. Operational restriction

Deep slicing remains a major challenge for fiber bundle systems, especially in applications that require accurate imaging of layered tissues. Unlike advanced modes such as optical coherence tomography (OCT) that provide intrinsic depth information, FBE relies on external scanning and reconstruction to achieve a limited degree of optical slicing. This limitation is particularly pronounced in dense or highly scattered tissues, where a lack of depth resolution can obscure key diagnostic features.

In addition, the physical flexibility and small diameter of fiber bundles make them suitable for navigating complex anatomical structures, but introduce operational complexity. Direct contact with soft tissue can cause deformation and misalignment, complicating imaging and interpretation. During use, misalignment or bending of the beam can cause geometric distortion of the image, which reduces the accuracy of diagnosis. As a result, precise calibration is required for changes in specific optical fibers, however, devices often need to be recalibrated as time changes or the environment changes.

* + 1. Data and computing challenges

Since a single session can generate thousands of high-resolution frames, this is especially true in dynamic clinical environments where continuous imaging is required. Therefore, processing and analyzing these large data sets in real time requires the use of advanced computing resources and efficient algorithms. Tasks such as image stitching, artifact removal, and pattern recognition often involve computationally expensive operations that are difficult to perform in a real-time clinical work environment.

In addition, the irregular arrangement of fiber cores in the bundle complicates the interpolation and reconstruction process. Techniques such as Fourier domain filtering, bilinear interpolation, and advanced machine learning models have been used to solve these problems. But most current methods struggle to balance computational efficiency with the high-quality image reconstruction required for accurate diagnosis.

* 1. Current Image Optimization Program
     1. Multi-frame super resolution algorithm

This method improves image quality by capturing multiple frames of the same tissue area at slightly different fiber bundle directions, such as rotation or shift. Redundant information in overlapping frames helps fill sampling gaps, mitigate artifacts, and improve resolution (Eadie et al., 2023). This method starts with frame acquisition and makes different fiber cores sample different parts of the tissue by rotating or translating the fiber bundle. The frame is then aligned with the common reference by a feature extraction and registration algorithm, while the motion artifacts are corrected (Eadie et al., 2023). Super-resolution algorithms typically utilize convolutional neural networks (CNNS) to reconstruct high-resolution images in the form of combined frames (Eadie et al., 2023). Subpixel reconstruction and artifact suppression are performed simultaneously, resulting in sharper images and reduced honeycomb patterns.

The main advantage is that the honeycomb effect is significantly suppressed and a clear image can be produced (Eadie et al., 2023). Moreover, the overlapping information of multiple frames can enhance the spatial resolution, make the tissue details clearer, and facilitate better identification of pathological features.

* + 1. Superposition method

The principle is to take multiple images of the same tissue area while slightly changing the position of the fiber bundle, for example by panning or rotating (Lee & Han, 2013). This allows different fiber cores to sample overlapping parts of the region, filling the gap left by discrete sampling of the fiber bundles.

After image acquisition, the frames are aligned using feature detection and registration techniques (Lee & Han, 2013). Algorithms such as SIFT or ORB identify consistent features between frames and calculate transformations such as homography to ensure precise alignment (Lee & Han, 2013). The aligned frames are then blended using intensity averaging, maximum intensity projection, or weighted blending. Thus, the honeycomb artifacts can be suppressed and the resolution can be improved (Lee & Han, 2013).

This method can reduce artifacts, improve spatial resolution and significantly improve image quality. Although it is computationally heavy, it has been proved that real-time applications can be achieved through optimization algorithms.

* + 1. PyFibreBundle

PyFibreBundle is an open source Python package specifically designed to solve challenges in imaging beam systems (Hughes, 2023). These systems encounter problems such as low resolution, honeycomb artifacts, and uneven lighting. PyFibreBundle provides a comprehensive set of tools to improve image quality and make post-processing of FBE μimages more efficient (Hughes, 2023).

PyFibreBundle contains pre-designed filters and customizable options to reduce small honeycomb artifacts (Hughes, 2023). The filter is optimized to suppress periodic artifacts while preserving the true characteristics of the imaged tissue. By utilizing spatial interpolation technology, PyFibreBundle fills the gaps between the fiber cores, a process that smooths out the image and restores continuity.

The advantage of PyFibreBundle is that it improves the quality of the FBEμ image, making it easier to interpret clinical diagnoses (Hughes, 2023). By reducing artifacts and increasing resolution, doctors can better identify pathological features in the tissue.

* 1. The solution selected in this study

Among the various methods proposed so far (such as frequency domain filtering, core interpolation or image superposition, etc.), the interpolation-based method is the simplest and most effective method, and it can preserve the original core information. Compared with other methods, core interpolation can take into account both image quality and computational cost, and is widely used in clinical and commercial systems.

The basic principle of interpolation is to use the grayscale values ​​of the sampling points as known data points and estimate the unknown areas between them through interpolation. Thus, on the basis of maintaining the original image information, the gaps are filled and a more continuous and natural image structure is reconstructed. Compared with other image processing methods, the interpolation method can smoothly transition the unknown area information on the basis of preserving the image information, and the damage to the image structure is small.

The widely used open source library PyFibreBundle uses the triangular linear interpolation method, which is computationally efficient and can obtain good interpolation results. However, due to its lack of high-order continuity, fine image details may be lost. And grayscale jumps may occur in areas where the fiber core is unevenly distributed.

To address these limitations, this study selected spline function-based interpolation as a high-order alternative. Spline interpolation can provide smooth transitions and better image quality, especially when dealing with tiny tissue structures. The continuity of spline functions makes them important in edge preservation and smooth transitions. This study is built on the modular framework of PyFibreBundle, based on its core detection. On this basis, a spline interpolation module is designed to replace the default linear interpolation with the spline interpolation method. This method can flexibly expand new functions while ensuring compatibility with existing libraries.

1. Material and Methods
   1. Project Objective

The main goal of this project is to optimize fiber bundle endoscope image processing through spline interpolation method, including the following aspects:

1. Improve image quality: Combine contrast enhancement and other methods to improve image clarity and visualization.
2. Effectively remove honeycomb artifacts: Design a special filtering method based on spline interpolation to remove periodic honeycomb artifacts in fiber bundle images. Compare the artifact removal performance of different interpolation methods (such as B-spline and cubic spline) and select the best solution.
3. Improve image processing speed: Implement an efficient spline interpolation algorithm and optimize the code structure to reduce running time.
   1. Tool introduction
      1. OpenCV

OpenCV (Open Source Computer Vision Library) is a powerful open source computer vision and image processing library introduced by Intel in 1999. It is a high performance, easy to use and free tool set for academic research and industrial applications. OpenCV contains more than 2,500 optimization algorithms, supports multiple operating systems and programming languages, and can be flexibly integrated into a variety of projects. As a modular library, OpenCV divides functionality into modules such as basic image processing, feature detection and matching, machine learning, and video analysis. The design facilitates function expansion and improves development efficiency.

Because of its unique fiber bundle structure, honeycomb artifacts and other distortions often appear in FBE images. At the same time, due to the limitation of optical fiber density, the resolution is also affected. In this study, OpenCV image processing module is used to optimize the image quality through a variety of algorithms.

* + 1. PyFibreBundle

PyFibreBundle is an open source Python library specially designed for processing fiber beam endoscope images. Its main function is to realize the correction, enhancement and reconstruction of the original image acquired by fiber beam endoscope. The library, developed by researchers at the University of Bath in the United Kingdom, aims to simplify tasks such as honeycomb artifact removal and fiber bundle image reconstruction that are common in fiber bundle endomicroscopy image processing.

The project focuses on PyFibreBundle 's core functionality: fiber bundle Calibration, which automatically identifies the position of each fiber by collecting standard reference images, and creates a fiber positioning Mask. This project is modified in the framework of the PyFibreBundle function, using spline interpolation instead of trigonometric linear interpolation.

* + 1. SciPy

SciPy (Scientific Python) is an efficient and powerful open source library for scientific computing in Python. Based on NumPy, SciPy provides a wealth of mathematical, scientific, and engineering computational tools for a wide range of applications in data processing, image analysis, signal processing, and numerical optimization.

Its main advantage is that it can provide a wealth of interpolation algorithms, including linear, Cubic spline (Cubic spline), B-Spline interpolation. The project uses SciPy spline interpolation functions in the code section.

* 1. Introduction to Spline interpolation algorithm

Spline interpolation is a smooth interpolation method that connects data points through piecewise polynomial functions and is widely used in image and signal processing. Compared with common linear interpolation or polynomial interpolation, spline interpolation can achieve smoother and more natural interpolation effects by setting continuity constraints between segments. In fiber bundle endomicroscopy image processing, b-splines and cubic splines can effectively reconstruct continuous tissue structures destroyed by honeycomb artifacts.

* + 1. Cubic Spline

Set up a set of nodes:

Construct a set of spline function , Between two adjacent nodes , define a cubic polynomial:

The constraints include:

The interpolated values ​​at each node are equal:

The first-order derivatives at the nodes are equal:

The second-order derivatives at the nodes are equal:

* + 1. B-Spline

B-spline constructs interpolation curves through basis functions.

B-spline is defined as:

is the kth order B-spline basis function

is the weight of the control point

is the order of the spline (e.g. = 3 represents a cubic spline)

Recursive formula (Cox-de Boor formula):

Initial definition of basis functions:

The recursive formula is:

* + 1. Advantages of spline interpolation

Spline interpolation not only has continuous function values ​​at each node, but also continuous derivatives and second-order derivatives, making the interpolation curve very smooth. Moreover, B-spline interpolation is a local interpolation, and modifying a control point will only affect its adjacent curve segments without changing the overall curve shape.

* 1. Operation procedure

In this study, all methods are implemented based on a unified code framework, which mainly includes two modules.

* + 1. Calibration module

Load the original endoscopic image and remove the noise interference of the image edge or non-fiber bundle area through automatic mask processing to provide clean input for subsequent core point detection. And extract the coordinate information of each core in the fiber bundle, automatically determine the center position and fiber bundle radius. Then call init\_spline\_interp for initialization (including background and normalization parameter calculation).

* + 1. Reconstruction module

Implement the process of spline interpolation reconstruction. Use the extracted core points to obtain the grayscale value or color value of the core area in the original image. If there is a background image and a normalized image, the core grayscale value is processed accordingly. According to the pre-designed size parameters, a coordinate grid of the reconstructed area to be interpolated is established. Then the method in scipy is used for spline interpolation, and the reconstructed image is masked.

The whole process is shown in the figure below.

* 1. Code Detail
     1. calib\_spline\_interp Function

**Input parameters:**

img: original calibration image (single channel or color).

coreSize: parameter used to estimate the fiber core spacing, which is convenient for subsequent core detection.

gridSize: specifies the size of the reconstructed output image (the image is square).

**Step description:**

1. Automatic mask processing: If the autoMask parameter is set, call pybundle.auto\_mask to mask the input image and remove the background interference area.
2. Core point extraction: Use the pybundle.find\_cores method to obtain the x and y coordinates of all core points in the fiber bundle. The coordinates are rounded and converted to integers for subsequent processing.
3. Automatic calculation of center and radius: If the center position (centreX, centreY) or radius is not specified, the center is determined by calculating the mean of all core points, and the fiber bundle radius is determined by calculating the maximum distance from each point to the center.
4. Initialize interpolation parameters: Call the init\_spline\_interp function to complete the initialization of information; calculate background and normalization information, generate masks required for interpolation, etc.

Output:

Returns an instance of the BundleCalibration class, which contains data such as core point location, interpolation area parameters, background and normalization information.

* + 1. init\_spline\_interp function

This function first determines whether the image is in color, so that different processing can be performed according to the number of channels. Then the background and normalization values ​​are calculated, and the information of each core point is stored in the calibration object. For both background and normalization operations, pybundle.core\_values ​​is called. This function is responsible for extracting the corresponding pixel value at each core point for subsequent interpolation. If the mask parameter is set, a mask is used for the output interpolated image to limit the image to the fiber bundle area.

* + 1. recon\_spline\_interp function

**Input parameters:**

img: the original endoscopic image to be reconstructed by interpolation.

calib: the BundleCalibration object obtained by the previous calibration module, which contains the necessary core points and geometric information.

**Main steps:**

1. Core grayscale value extraction: use the pybundle.core\_values ​​function to extract the pixel values ​​of each core point from the original image.
2. Background subtraction and normalization: if a background image is provided, the pixel values ​​extracted from the core points are subtracted from the background. If normalization is set, it is converted proportionally so that the brightness of the interpolated image corresponds to the standard range (0-255).
3. Construct interpolation grid: construct a two-dimensional grid based on the center point and fiber bundle radius calculated during calibration; this grid covers a square area with the center of the fiber bundle as the origin and a side length of gridSize. Generate interpolation points (grid\_x, grid\_y) through numpy.meshgrid.
4. Cubic spline interpolation: Call the scipy.interpolate.griddata function and use method='cubic' to implement cubic spline interpolation and map the pixel values ​​of the core points to the entire interpolation grid. This step eliminates the honeycomb artifacts caused by fiber core sampling in the original endoscopic image.
5. Formatting: Reshape the generated interpolation array into an appropriate image matrix (such as a two-dimensional or three-dimensional array) according to the single-channel or multi-channel characteristics of the image.

**Output:**

Return the image reconstructed by cubic spline interpolation. The image size is gridSize×gridSize. The color and detail restoration effects are normalized and the honeycomb artifacts are subtracted.

1. Results

To evaluate the effectiveness of spline interpolation in removing honeycomb artifacts in fiber bundle endomicroscopy images, a series of experiments were performed using calibration images and sample images obtained from the PyFibreBundle library.

* 1. Fiber core detection and calibration

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Fig. 9 Original background image

Figure 9 shows the original image with a visible honeycomb pattern, with no objects in the field of view, presenting a flat field image that is essentially undisturbed. The individual fiber cores can be clearly seen. Using the PyFibreBundle function, it can be determined that the average spacing of the fiber cores is 3.2µm. The result of manual measurement using ImageJ is 3.4µm, which is basically consistent with the result calculated by the function. Figure 10 shows the effect of superimposing the core positions detected by the pybundle.find\_cores() function on the image. The experimental results show that a total of 27,838 valid core points were detected, which are densely distributed and arranged in an approximately hexagonal shape.

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Fig. 10 Detected Fibre Cores Overlay

* 1. Mask preprocessing

In order to avoid the influence of the background outside the circular area of ​​the fiber bundle and improve the accuracy of the core positioning, the image is automatically masked (auto\_mask) before detection to exclude the non-core area at the edge of the image. Figure 11 shows the image result after mask processing, and the background outside the circular area of ​​the fiber bundle has been effectively suppressed.

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Fig. 11 Masked Fiber Bundle lmage

* 1. Removing artifacts by cubic spline interpolation

According to the detected core position and the extracted core grayscale value, the image is reconstructed by cubic spline interpolation. The interpolation result is displayed on a square image of size gridSize × gridSize. Figure 12 shows the reconstructed image, the image structure is more continuous, and the honeycomb structure is basically smoothed out. To intuitively demonstrate the image reconstruction effect, the original image and the reconstructed image are compared side by side. Figure 12 clearly shows the significant improvement of the reconstructed image in terms of image continuity, edge structure and visual quality.

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Fig. 12 This study is compared with the original image

* 1. Comparative analysis of triangular linear interpolation and cubic spline interpolation

To further evaluate the effectiveness of the proposed cubic spline interpolation method, this section quantitatively and qualitatively compares it with the triangular linear interpolation method used by default in the PyFibreBundle library. The image reconstruction uses the same original image and fiber core position input, and the output image size is 800\*800 to ensure the fairness of the comparison.

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Fig. 13 This study is compared with trigonometric linear interpolation

Figure 13 shows the reconstructed images generated by the two interpolation methods. From the subjective visual effect, the triangular linear interpolation method has the problem of blurred boundaries while maintaining the overall structure of the image. The proposed cubic spline interpolation method performs better in terms of image smoothness, the image structure is more continuous, the transition of the background area is more natural, and the visual quality is higher. Figure 14 shows a partial enlargement of the two reconstructed images.

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Fig. 14 Partial enlargement

In addition, in terms of code running speed, the running speed of the cubic spline interpolation code is 54.4% faster than that of the triangular linear interpolation method. Figure 15 shows the time required for the two codes to run. From the data and images, the cubic spline interpolation performs well in terms of image detail preservation and structural consistency, and has low computational complexity.

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Fig. 15 Code running time

To quantify the interpolation quality of the two methods, this study calculated the peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) of the reconstructed image. The results are shown in Figure 16. The two methods are close in SSIM value, both around 0.21, indicating that they are equivalent in terms of structure preservation ability. The PSNR index of the two methods is slightly higher than 4 dB, indicating that there is a certain difference between the reconstructed image and the original image, but this is a typical information loss caused by resampling. This shows that although the cubic spline interpolation is visually smoother, its overall reconstruction effect is not much different from that of the traditional triangular interpolation.

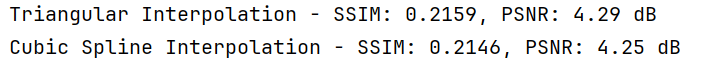


Fig. 16 SSIM and PSNR

1. Discussion
   1. Failed attempt

The spline interpolation function is the key to this study. This study has tried many interpolation schemes. After many failures and repetitions, the cubic spline interpolation was finally chosen as the solution. The following is a brief overview of the schemes that this study has tried.

* + 1. IDW interpolation

Inverse distance weighting (IDW) is a distance-based spatial interpolation method widely used in geographic information systems, precipitation prediction, terrain (geomorphology) mapping and other fields (Ikechukwu et al., 2017). Its core idea is to use the data of known points within a certain range around the interpolation point for interpolation. The closer the known point is to the interpolation point, the greater the impact on the interpolation result.

Since the information of fiber bundle endoscope images is mainly concentrated in the center of the fiber bundle, but the arrangement of the fiber bundle is not completely regular. IDW is an interpolation method directly based on discrete points, which is more suitable for processing irregular data. Moreover, IDW can use more information of points (the nearest k points) by expanding the maximum neighborhood range and can obtain more accurate interpolation results compared to linear interpolation.

However, in actual application, it is found that IDW interpolation will lead to inaccurate final results due to the existence of outliers with a short distance. Blurring is easy to cause in areas where the fiber core arrangement is not completely regular, and a "halo" phenomenon appears on the edge of the image details. As shown in Figure 17. This leads to blurred image structure, especially difficulty in distinguishing tissue boundaries. In addition, when there are too many known points selected, IDW needs to traverse all selected points to calculate the distance, which greatly increases the time to run the code and the computational complexity is much higher than linear interpolation.

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Fig. 17 IDW interpolation results

* + 1. B-spline interpolation

Compared with traditional linear interpolation, B-spline interpolation achieves high-order smoothing effect by weighted combination of multiple low-order polynomials (Lyche, Manni and Hendrik Speleers, 2018). Therefore, B-spline has better image quality and smoothing effect. However, B-spline interpolation is often used to process regular two-dimensional data and is not suitable for interpolation of irregular scattered data. However, the core distribution of fiber bundles is not uniform, and its use is subject to certain restrictions.

To this end, this study first attempts to slice the original image by column, regard each slice as a one-dimensional signal, and perform one-dimensional B-spline interpolation on it. This method can achieve the effect of smooth interpolation in the one-dimensional direction. However, the arrangement of the core in two-dimensional space is irregular, and one-dimensional slicing cannot accurately reflect the actual spatial relationship between the cores. This leads to the introduction of more erroneous data in the interpolation process. The reconstructed Figure 18 shows obvious noise and jagged edges, especially in areas with drastic grayscale changes, the interpolation effect is significantly reduced.

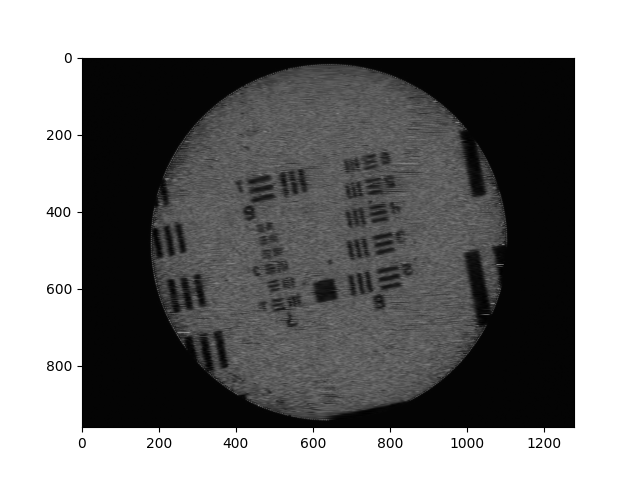


Fig. 18 B-spline interpolation results

On this basis, this study proposed a new improvement idea. Considering that the arrangement of fiber bundles presents a hexagonal structure locally, this study tried to use hexagonal units to segment the image area. And each fiber core is assigned a new coordinate position according to the hexagon to which it belongs. Through this method, the original irregular fiber core position is mapped to a regular two-dimensional grid, so that B-spline interpolation is used. However, the reconstructed image still has problems such as structural breaks and edge jaggedness.

* + 1. Nearest neighbor interpolation

In the further optimization process, this study tried to abandon the use of B-splines and use the nearest neighbor interpolation method based on the above coordinate framework. This method is simple to operate, and the reconstructed image retains a clearer structural outline. However, due to the lack of a smoothing mechanism, the reconstructed image has severe jagged edges and is difficult to meet the image requirements. Figure 19 shows the image after using the nearest neighbor interpolation.

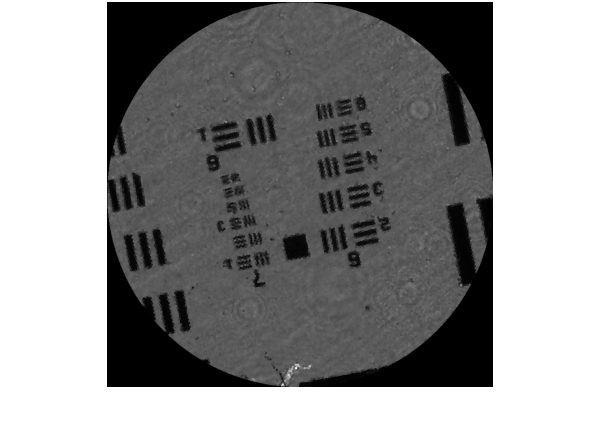


Fig. 19 Nearest Neighbor

* 1. Method advantages and innovation
     1. Innovation in algorithm design

Triangular linear interpolation is based on linear functions (C⁰ continuous), while cubic spline interpolation uses C² continuous polynomial functions. The continuity of the higher-order derivatives of cubic spline interpolation reduces the grayscale jump of linear interpolation at the junction of the fiber core, effectively reducing the blurring of the image edge. Moreover, the smoothness of the cubic spline makes the grayscale transition of the honeycomb gap closer to the real optical diffusion characteristics, making the image background smoother.

In addition, the code optimizes the module based on PyFibreBundle. If you need to use the new method, you only need to modify the recon\_spline\_interp() function, which reduces the cost of algorithm reproduction and migration.

* + 1. Performance advantages

Cubic spline interpolation does not rely on the irregular triangular part of triangular linear interpolation, which reduces the complexity of calculation, can effectively reduce the overhead of code runtime, and speed up the running speed. The image reconstruction time of cubic spline interpolation is shortened to 1 second compared with 2 seconds of triangular linear interpolation, and the running efficiency is improved by 50%. While improving visual quality, a 54.4% acceleration was achieved, which can significantly reduce the processing time of large-scale data sets in non-real-time scenarios.

* 1. Limitation Analysis

Although the image reconstruction method based on cubic spline interpolation proposed in this study shows good results in visual quality and operating efficiency, there are still some limitations that cannot be ignored.

* + 1. Limitations of quantitative evaluation indicators

In image quality assessment, this study uses two indicators, structural similarity index (SSIM) and peak signal-to-noise ratio (PSNR), as a means of measuring the similarity between the interpolated image and the original image. However, since the original image itself has serious honeycomb artifacts, it does not represent the real tissue structure. Therefore, the values ​​reflected by SSIM and PSNR must have a significant deviation. This leads to the fact that in most cases, even if the visual effect of the reconstructed image has been significantly improved, SSIM/PSNR has failed to effectively reflect its advantages in terms of image. Therefore, the current quantitative evaluation is somewhat subjective and lacks an accurate measurement of the degree of optimization of the real image.

* + 1. Limitations of smooth interpolation algorithms for complex tissue structures

Cubic spline interpolation performs well in reconstructing general grayscale transition areas, but when processing images with complex tissue edges, it may make important structures difficult to distinguish due to excessive smoothing, reducing the anatomical authenticity of the image. Excessive smoothing may affect texture- or edge-based image analysis.

* + 1. Limitations of experimental data volume

Currently, the experiment is mainly verified based on the data set provided by PyFibreBundle. The data scale is small, the image type is relatively single, and there is a lack of systematic testing under different tissue types and different imaging conditions. Therefore, the adaptability and stability of the method proposed in this study in complex clinical scenarios still need further evaluation.

1. Conclusion and Future Work
   1. Conclusion

This study aims to improve the image quality of fiber bundle endoscopes, focusing on eliminating honeycomb artifacts caused by the inherent structure of the fiber core. In order to solve the honeycomb artifacts of FBE images, this study implemented several interpolation-based image reconstruction methods. Among them, cubic spline interpolation is the most effective method. This study implemented fiber bundle endoscope image reconstruction based on cubic spline interpolation by applying OpenCV and SciPy, using a code framework designed based on PyFibreBundle.

The results show that cubic spline interpolation can effectively smooth honeycomb artifacts while retaining the original image information. Compared with the triangular linear interpolation method provided by PyFibreBundle, this method has improved visual quality and computational efficiency, with an image processing speed of 54.4% and a clearer image structure.

In addition to cubic spline interpolation, this paper also records a series of exploratory methods that were evaluated and eventually eliminated due to poor interpolation results. These negative results are valuable because they are explorations on the road to success and can provide reference for future method selection.

* 1. Future Work

The method developed in this study has achieved certain results, but there are still some limitations and opportunities for further improvement.

* + 1. Improving operational efficiency

One of the most important goals in the future is to improve the current algorithm to enable real-time operation of images. Real-time operation is crucial in clinical settings and can effectively help doctors perform minimally invasive surgery or in vivo examinations. Although the computational efficiency of cubic spline interpolation has made great progress, it may be necessary to achieve real-time operation through Numba or GPU acceleration.

* + 1. Combining with deep learning

Convolutional neural networks (CNNs) can be used to enhance the spline interpolation effect by correcting residual artifacts. Combining spline interpolation as an initialization step with deep learning can provide new hybrid solutions.

* + 1. Testing with a wider range of datasets

In order to be used in practical applications, this study should be evaluated using more diverse and clinically relevant datasets. The stability of the algorithm in different clinical environments can be verified by acquiring data under different organs, lighting, and noise conditions.

* + 1. Improving evaluation metrics

In this study, SSIM and PSNR were used to evaluate the quality of image reconstruction. However, these metrics have certain limitations and cannot well reflect whether there are artifacts in the reconstructed image. Therefore, a visual scoring study was conducted with expert doctors. Develop specific metrics to assess image reconstruction quality. This will provide a more meaningful assessment of clinical utility than numerical similarity.

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