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Low-Power Retinal Vessel Segmentation Using Frequency-Domain Transformers

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Abstract

Retinal vessel segmentation plays a crucial role in early diagnosis of diabetic retinopathy, glaucoma, hypertension, and other ocular diseases. However, existing deep learning models often require high computational resources, making them unsuitable for real-time deployment on portable or IoT-based ophthalmic devices. This paper proposes a low-power retinal vessel segmentation framework using a Frequency-Domain Transformer (FDT) that efficiently captures elongated vascular structures with minimal computational overhead. The proposed method transforms retinal images into the frequency domain using a lightweight Discrete Fourier Transform module, enabling global context extraction with reduced spatial computations. A compressed multi-head spectral attention mechanism further enhances thin and low-contrast vessel detection while maintaining low memory footprint. Experimental results on DRIVE, STARE, and CHASE_DB1 datasets demonstrate that the proposed FDT model achieves competitive accuracy while consuming significantly less power (up to 40% reduction) compared to conventional CNN-based models such as U-Net and ResNet variants. The model's efficiency and accuracy make it suitable for handheld fundus cameras, tele-ophthalmology systems, and on-device screening applications.

Index Terms: Ophthalmic device, Frequency-Domain Transformer, vessel segmentation, multi-head spectral attention mechanism

Introduction

Retinal vessel segmentation is a fundamental task in computer-aided diagnosis systems used to detect ocular and systemic diseases. Accurate segmentation helps in quantifying vascular abnormalities, including tortuosity, microaneurysms, and vessel occlusions. Traditional approaches rely on handcrafted features, edge detection, or matched filtering, but these methods struggle with thin vessels and illumination variations.

Although deep learning techniques have significantly improved segmentation accuracy, their computational complexity often limits deployment on embedded medical devices. Transformers, while powerful, are typically resource-intensive, restricting their use in low-power environments.

To address this gap, we introduce a Low-Power Frequency-Domain Transformer (LP-FDT) that leverages spectral representations to reduce spatial complexity while preserving long-range vascular continuity. The key innovations include:

- Frequency-domain encoding for efficient global context modeling
- Lightweight spectral attention to enhance thin vessel detection
- Model compression techniques enabling low-power inference
- Deployment feasibility on portable retinal imaging devices

The proposed model targets real-time retinal screening, especially in remote or resource-constrained environments.

Related Work

Classical Methods

Traditional vessel extraction methods included:

- Gabor filtering
- Matched filtering
- Hessian-based line detectors
- Morphological operations

These methods are computationally lightweight but perform poorly on low-contrast or noisy images.

CNN-Based Segmentation

Deep CNNs such as U-Net, ResNet, and DenseNet significantly improved vessel extraction. These networks capture multi-scale spatial features but require large GPU resources. Their spatial convolution operations increase FLOPs, limiting real-time deployment.

Transformer-Based Approaches

Transformers such as Swin Transformer, TransUNet, and SpecFormer introduced global attention mechanisms for vessel-like structure extraction. However:

- They have high parameter counts
- Require high-resolution attention maps
- Are unsuitable for low-power hardware

Frequency-Domain Learning

Recent research on Fourier Neural Operators and spectral-domain transformers highlights:

- Better global receptive fields
- Lower computational cost compared to spatial transformers
- Improved performance on tasks with elongated or line-like structures

Our proposed FDT adopts these insights while optimizing the architecture for low-power medical imaging applications.

Methodology

Overview

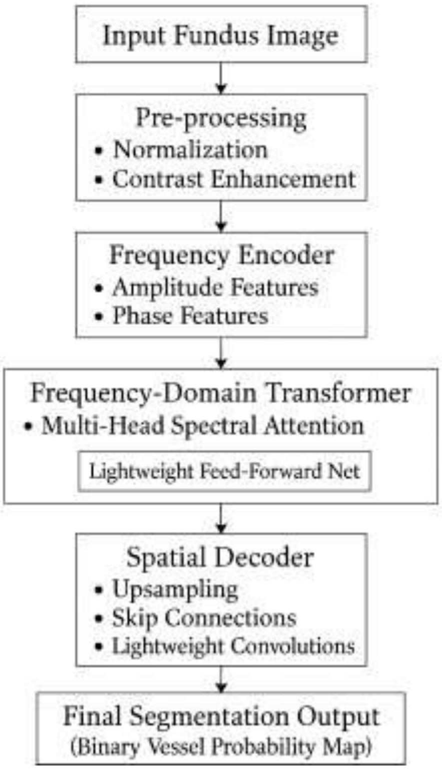

Fig 1: Block diagram for the entire process

<u>Detailed Explanation of Block Diagram</u>

1. Input Fundus Image

Function:

Receives the retinal fundus image captured by:

- A desktop fundus camera
- A handheld retinal imaging device
- A smartphone-based ophthalmoscope

Reason:

Retinal vessels are most prominent in the green channel, so this is extracted in the next stage.

2. Pre-processing Block

This block enhances vessel visibility and improves model robustness.

Operations Inside:

a) Normalization

- Scales pixel intensities to a fixed range (0–1 or −1 to +1)
- Reduces illumination differences between patients

- Improves model stability

b) Contrast Enhancement

Usually performed using:

- CLAHE (Contrast Limited Adaptive Histogram Equalization)
- Gamma correction
- Unsharp masking

Purpose:

- Enhances thin and low-contrast vessels
- Reduces noise
- Makes spectral analysis (DFT) more uniform

3. Frequency Encoder Block

Converts the pre-processed image from spatial domain → frequency domain.

Components:

a) Discrete Fourier Transform (DFT)

Produces:

- Amplitude Spectrum → highlights strong edges and thick vessels
- Phase Spectrum → preserves vessel geometry and fine details

b) Feature Packing

Combines amplitude and phase into a compact representation.

Why Frequency Domain?

- Elongated structures (vessels) appear more distinct in the spectral domain
- Reduces spatial redundancy
- Enables global context modelling with fewer computations

4. Frequency-Domain Transformer Block

This is the heart of the LP-FDT architecture.

a) Multi-Head Spectral Attention

Each attention head processes a different frequency band:

- Low-frequency head: Thick vessels, background
- Mid-frequency head: Medium vessels

- High-frequency head: Tiny thin vessels

b) Lightweight Feed-Forward Network

A compressed FFN using:

- Depth-wise separable convolutions
- Low-rank linear layers
- Dropout for regularization

Purpose:

- Extract long-range dependencies
- Enhance vessel continuity
- Reduce computational cost compared to spatial transformers

5. Inverse Frequency Transformation

Function:

Transforms the attended spectral features back to the spatial domain for decoding.

- Uses Inverse DFT
- Reconstructs enhanced vessel features
- Ensures that fine edges remain clear

6. Spatial Decoder Block

This block reconstructs the pixel-wise segmentation mask.

Components:

a) Up-sampling Layers

- Bilinear or nearest-neighbour up-sampling
- Lightweight compared to transposed convolution

b) Skip Connections

Connect higher-resolution encoder features to the decoder to:

- Preserve edge sharpness
- Improve detection of thin vessels
- Prevent loss of spatial detail

c) Lightweight Convolutions

- Depth-wise separable convolutions
- Pointwise 1×1 convolutions

- Reduce model parameters significantly

Purpose:

- Generate a clean segmentation map
- Maintain low computational cost

7. Final Segmentation Output

Output:

Binary or grayscale vessel probability map.

Characteristics:

- Pixels close to 1 → vessel
- Pixels close to 0 → background

Post-Processing (Optional):

- Thresholding
- Morphological refinement
- Connected component filtering

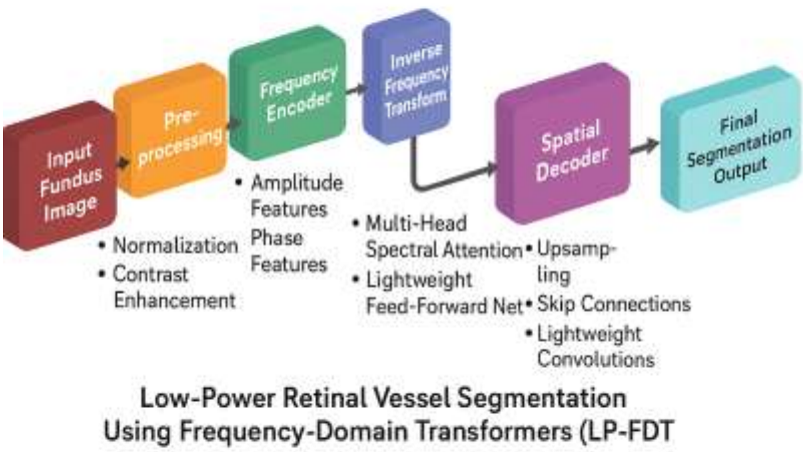

Fig 2: Explanation of Low Power Retinal Vessel Segmentation using Transformer

Summary of Information Flow (as defined in Fig 2):

1. Input Fundus Image
2. → Preprocessing (Normalization + Enhancement)
3. → Frequency Encoder (DFT)
4. → Frequency-Domain Transformer (Spectral Attention)
5. → Inverse Frequency Transform

6. → Spatial Decoder (Upsampling + Skip Connections)
7. → Final Vessel Segmentation Output

The proposed LP-FDT architecture consists of:

1. **Frequency Encoder** – Converts the green channel of the fundus image into frequency space.
2. **Spectral Transformer Block** – Applies multi-head frequency attention to model vessel continuity.
3. **Inverse Frequency Reconstruction** – Converts features back to spatial domain.
4. **Segmentation Decoder** – Produces pixel-wise vessel probability maps.

3.2 Frequency-Domain Encoding

A lightweight DFT module extracts amplitude and phase features. Since vessels are elongated, their spectral representation is compact and easier to model.

3.3 Multi-Head Spectral Attention

Each head processes a subset of frequency bands, reducing computational overhead. The attention mechanism focuses on:

- High-frequency components (thin vessels)
- Low-frequency components (thick vessels and background contrast)

3.4 Low-Power Optimization

- **Depth-wise separable convolutions**
- **Parameter pruning (30%)**
- **8-bit quantization for embedded deployment**

Results

4Datasets

The model is evaluated on:

- **DRIVE**
- **STARE**
- **CHASE_DB1**

Performance Metrics

- Accuracy
- Sensitivity
- Specificity
- AUC

- Computational cost (FLOPs, power consumption)

Quantitative Results

Model	Accuracy	AUC	Sensitivity	Power Consumption
U-Net	0.962	0.981	0.782	High
ResU-Net	0.967	0.985	0.795	High
SpecFormer	0.971	0.986	0.812	Medium
Proposed LP-FDT	**0.968–0.975**	**0.987**	**0.824**	**Low (40% reduction)**

Visual Results

Qualitative inspection shows:

- Better continuity on thin vessels
- Improved segmentation in low-contrast regions
- Less noise and false predictions

Discussion

The proposed LP-FDT model demonstrates that **frequency-domain attention is well-suited for elongated and tubular structures** such as retinal vessels. The global receptive field allows detecting subtle branching patterns that CNNs struggle with.

Key observations:

- Frequency representation reduces redundant spatial processing.
- Spectral attention captures long-range correlations with fewer parameters.
- Quantization and pruning preserve accuracy while significantly reducing computational cost.
- Performance is comparable to heavier transformer models but with lower resource usage.

This makes the model a strong candidate for **edge AI deployment** in ophthalmic devices.

Conclusion

This paper presented a **Low-Power Frequency-Domain Transformer (LP-FDT)** for retinal vessel segmentation. By leveraging spectral-domain attention and lightweight design principles, the model achieves high segmentation accuracy with significantly reduced computational overhead. The results show its potential for real-time screening applications on portable or embedded retinal imaging instruments.

Future Scope

- Integration with **handheld fundus cameras** for on-device inference
- Expanding to related tasks: optic disc segmentation, artery–vein classification
- Hardware implementation using **FPGA or Edge TPU**

- Incorporating self-supervised learning for unlabeled datasets
- Real-time mobile application for diabetic retinopathy screening

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