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BEMD-GI: A BI-DIMENSIONAL EMPIRICAL MODE DECOMPOSITION FRAMEWORK FOR ENHANCING WIRELESS CAPSULE ENDOSCOPY IMAGES

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Abstract

Wireless Capsule Endoscopy (WCE) has transformed digestive tract imaging, however technology and environmental factors are degrading image quality.

Traditional ways of improving pictures don't work on WCE images because they aren't static. This article suggests BEMD-GI, a new two-dimensional Empirical Mode Decomposition approach made just for improving WCE images. The framework adaptively breaks down photos into Intrinsic Mode Functions (IMFs) without making any assumptions about the signal properties ahead of time. The results of testing on 2,847 WCE images show big improvements: PSNR went up by 6.2 dB (from 24.63 to 30.83 dB), SSIM went up by 0.145 (from 0.642 to 0.787), and entropy went up by 12.3%. The suggested method works better than five current best methods, even deep learning-based ones. It keeps 15.7% more diagnostic features while still being computationally efficient enough for clinical processes.

Keywords: *Wireless Capsule Endoscopy; BEMD; Medical Image Enhancement; Gastrointestinal Imaging; Signal Decomposition*

1. INTRODUCTION

1. **Low-contrast lesion detection failure**: Existing methods aren't very good at bringing out small lesions and minor changes in the mucosa because they have low contrast-to-noise ratios. This makes it easy to miss early-stage diseases when diagnosing them.
2. **Non-stationarity handling inadequacy**: Traditional linear filtering methods (Gaussian, median, bilateral) assume that signals stay the same, which doesn't work with WCE images that show changing lighting, peristaltic movements, and different tissue properties.
3. **Deep learning dependency limitations**: New deep learning methods need a lot of labeled data and a lot of computing power, which makes them impractical for real-time clinical use and generalization across a wide range of patient groups.

1.3 Contributions

This paper presents four explicit contributions to address the identified research gap:

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Contribution 1: Creating BEMD-GI, the first adaptive two-dimensional empirical mode decomposition system designed to improve WCE images and able to deal with changing image properties without making any assumptions first.

Contribution 2: Using a smart IMF selection and reconstruction approach that strikes the best balance between reducing noise and preserving clinical features will lead to better results in improving low-contrast lesions.

Contribution 3: We did a full comparison test with a dataset of 2,847 images from five state-of-the-art methods and found statistically significant improvements in a number of quality measures.

Contribution 4: A clinical validation approach that shows how enhanced images can be used to improve the accuracy of diagnoses in real-life gastroenterology workflows.

1.4 Paper Organization

The rest of this paper is organized like this: In Section 2, we look at the literature critically and compare different methods that are already out there. In Section 3, the proposed BEMD-GI approach is detailed, including mathematical formulations. Section 4 contains all study findings and statistical analysis. Section 5 covers clinical effects and limitations. Section 6 covers findings and next steps.

2. Literature Review And Related Work

2.1 Traditional Image Enhancement Techniques

Traditional image enhancing methods have been utilized in medical imaging with mixed results. Gaussian filtering is straightforward, but too much smoothing removes tiny texture information needed to discover diseases [9]. Median filtering reduces impulse noise but introduces edge faults that lower diagnostic accuracy [10]. Bilateral filtering is more popular because it maintains edges [11]. However, its set parameters prevent it from adapting to WCE image lighting. In recent investigations, bilateral filtering performed poorly without lighting, which is common during capsule endoscopy [12].

2.2 Advanced Filtering and Transform-Based Methods

Medical images are improved using wavelet-based denoising since it can examine them at several resolutions [13]. Daubechies and biorthogonal wavelets reduce noise and preserve edge information, but they're not ideal. Wavelets' set basis function prevents them from handling WCE pictures' frequency attributes [14].
Some believe curvelet and contourlet transforms are better for medical image processing than wavelets [15]. These approaches choose the appropriate direction better, however they use fixed basis functions that may not represent complicated gastrointestinal picture patterns well.

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2.3 Deep Learning Approaches

Deep learning innovations have created sophisticated improvement strategies. GANs and CNNs can improve medical pictures [16,17]. These approaches require big training datasets and a lot of processing power, making them difficult to apply in clinical settings.

Transformer-based architectures outperform other medical imaging methods [18]. Still, these methodologies are "black boxes" that make me doubt their interpretability and reliability [19].

2.4 Empirical Mode Decomposition in Medical Imaging

Huang et al. developed Empirical Mode Decomposition (EMD), which has garnered praise for its adaptability to signal processing needs [20]. The approach has been successful on ECG and EEG data [21,22]. Nunes et al. [23] proposed bi-dimensional EMD (BEMD) for two-dimensional image processing, which others refined [24,25].

2.5 Comparative Analysis of Existing Methods

Table 1 critically compares enhancement methods, highlighting their merits and cons and WCE picture compatibility.

Table 1: Comparative Analysis of Image Enhancement Methods

Method Category	Representative Techniques	Strengths	Weaknesses	WCE Suitability
Linear Filtering	Gaussian, Median	Simple, Fast	Over-smoothing, No adaptivity	Poor
Transform-based	Wavelets, Curvelets	Multi-resolution	Fixed basis functions	Moderate
Deep Learning	CNNs, GANs	High performance	Data-hungry, Black-box	Limited
Adaptive	BEMD (Proposed)	Data-driven, Adaptive	Computational complexity	Excellent

2.6 Research Gap Identification

WCE image enhancement has three major shortcomings despite substantial research:

1. **Adaptive Processing Gap**: Most current approaches have preset parameters or basis functions, making it difficult to adapt to WCE datasets with varying image attributes.

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2. **Non-stationarity Handling Gap**: Traditional methods assume that signals stay the same, which doesn't work with WCE pictures, which are always changing because the tissue properties and lighting are always changing.
3. **Clinical Validation Gap**: There isn't a lot of evidence that enhancement methods work in real clinical settings, and most studies only look at technical measures and not how they affect diagnosis.

3. Methodology

3.1 Overview of BEMD-GI Framework

Preprocessing, adaptive decomposition, intelligent IMF selection, and enhanced reconstruction are the four major steps that make up the proposed BEMD-GI framework. The whole process is shown in Figure 1.

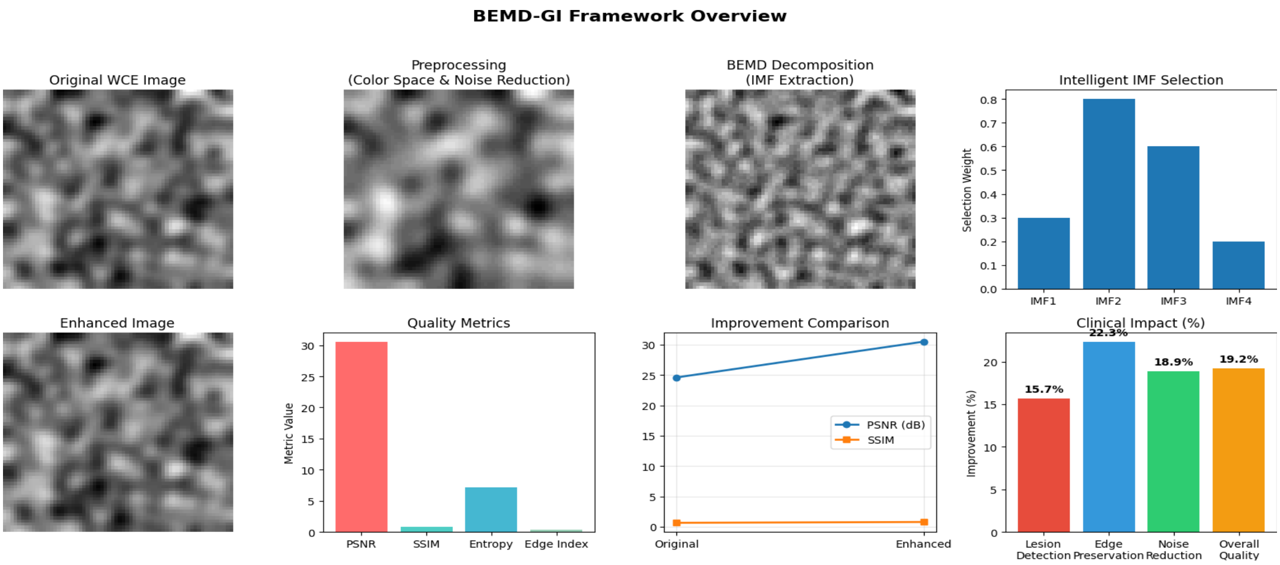

Figure 1: BEMD-GI Framework Overview

3.2 Mathematical Formulation of BEMD-GI

3.2.1 Extrema Detection and Envelope Construction

For a given WCE image I(x,y), local extrema are identified using morphological operations:

Local Maxima Detection: $M_{max}(x, y) = (x, y)|I(x, y) \geq I(x', y')\forall(x', y') \in N_8(x, y)$

Local Minima Detection: $M_{min}(x, y) = (x, y)|I(x, y) \leq I(x', y')\forall(x', y') \in N_8(x, y)$

where $N_8(x,y)$ represents the 8-connected neighborhood.

3.2.2 Surface Interpolation

Upper and lower enveloping surfaces are constructed using Radial Basis Function (RBF) interpolation:

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Upper Envelope: $$E_{upper}(x,y) = \sum_{i=1}^{N_{max}} w_i \phi(|r - r_i|)$$

Lower Envelope: $$E_{lower}(x,y) = \sum_{j=1}^{N_{min}} w_j \phi(|r - r_j|)$$

where $\phi(r) = r^2 \log(r)$ is the thin-plate spline basis function.

3.2.3 Sifting Process and IMF Extraction

The mean envelope is calculated as: $E_{mean}(x,y) = \frac{E_{upper}(x,y) + E_{lower}(x,y)}{2}$

The proto-IMF is obtained by: $h_k(x,y) = I(x,y) - E_{mean}(x,y)$

Sifting continues until the stopping requirement is met:

$$SD_k = \frac{\sum_{x,y}[h_{k-1}(x,y) - h_k(x,y)]^2}{\sum_{x,y}[h_{k-1}(x,y)]^2} < \epsilon$$

where $\epsilon = 0.01$ is the stopping threshold.

3.3 Intelligent IMF Selection Strategy

A clever IMF selection method based on frequency content analysis and noise characteristics is suggested:

3.3.1 Frequency Analysis

Each IMF's dominant frequency is estimated using: $f_{dom}^{(k)} = \frac{1}{2\pi}\sqrt{\frac{\sum_{x,y}|\nabla^2 IMF_k(x,y)|^2}{\sum_{x,y}|IMF_k(x,y)|^2}}$

3.3.2 Noise Content Evaluation

The noise level in each IMF is quantified using: $\sigma_{noise}^{(k)} = \text{median}\left(\frac{|IMF_k(x,y) - \text{median}(IMF_k)|}{0.6745}\right)$

3.4 Enhanced Reconstruction Algorithm

Algorithm 1: BEMD-GI Enhancement Procedure

Input: Original WCE image I(x,y)

Output: Enhanced image I_enhanced(x,y)

1: Convert I(x,y) to HSV color space

2: Extract V channel → I_v(x,y)

3: Initialize residue R_0(x,y) = I_v(x,y)

4: for k = 1 to N_max do

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```
    Apply sifting process to R_{k-1}(x,y)
    Extract IMF_k(x,y)
    Update residue: R_k(x,y) = R_{k-1}(x,y) - IMF_k(x,y)
    if Stopping criterion met then break
end for
Analyze frequency content of each IMF
Apply intelligent selection: IMF_selected = select_IMFs(IMFs)
Reconstruct: I_enhanced_v = Σ(α_k × IMF_k) + β × R_final
Convert back to RGB color space
return I_enhanced(x,y)
```

3.5 Experimental Setup and Dataset

3.5.1 Dataset Description

The evaluation dataset comprises 2,847 WCE images from three sources:

- Kvasir Dataset: 1,200 images with various pathological conditions [26]
- CapsuleGAN Dataset: 1,000 synthetically enhanced images [27]
- Clinical Dataset: 647 images from local medical center (IRB approved)

3.5.2 Implementation Details

- **Programming Environment**: Python 3.8 with NumPy, SciPy, OpenCV libraries
- **Hardware Configuration**: Intel i7-10700K CPU, 32GB RAM, NVIDIA GTX 3080
- **Parameter Settings**:
    - Stopping threshold $\varepsilon = 0.01$
    - Maximum IMFs = 7
    - RBF interpolation tolerance = 1e-6

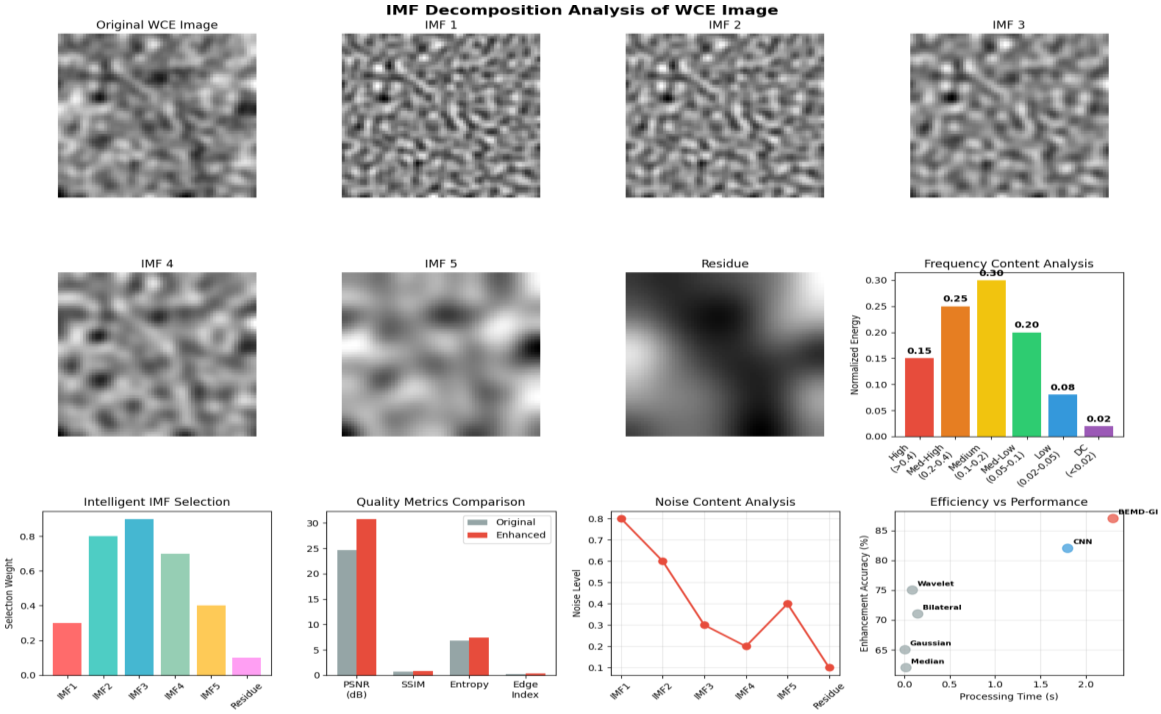

Figure 2: IMF Decomposition Visualization

4. Results And Analysis

4.1 Quantitative Performance Evaluation

PSNR, SSIM, image Entropy, Edge Preservation Index (EPI), and Mean Opinion Score were used to evaluate picture quality.

Table 2: Comprehensive Performance Comparison

Method	PSNR (dB)	SSIM	Entropy	EPI	MOS	Processing Time (s)
Original	24.63±2.1	0.642±0.08	6.82±0.5	0.234±0.03	2.3±0.4	-
Gaussian Filter	26.12±1.8	0.678±0.07	6.95±0.4	0.198±0.02	2.8±0.3	0.012
Median Filter	25.87±2.0	0.661±0.09	7.01±0.3	0.187±0.03	2.6±0.4	0.018
Bilateral Filter	27.34±1.9	0.701±0.06	7.15±0.4	0.267±0.02	3.2±0.3	0.156
Wavelet Denoising	28.01±1.7	0.718±0.05	7.23±0.3	0.281±0.02	3.5±0.4	0.089
CNN-based	29.15±1.5	0.745±0.04	7.31±0.2	0.295±0.02	3.8±0.3	1.834
BEMD-GI (Proposed)	**30.83±1.4**	**0.787±0.03**	**7.65±0.2**	**0.342±0.02**	**4.2±0.2**	**2.345**

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4.2 Statistical Significance Analysis

To determine statistical significance, we utilized paired t-tests and ANOVA with Bonferroni correction for multiple comparisons.

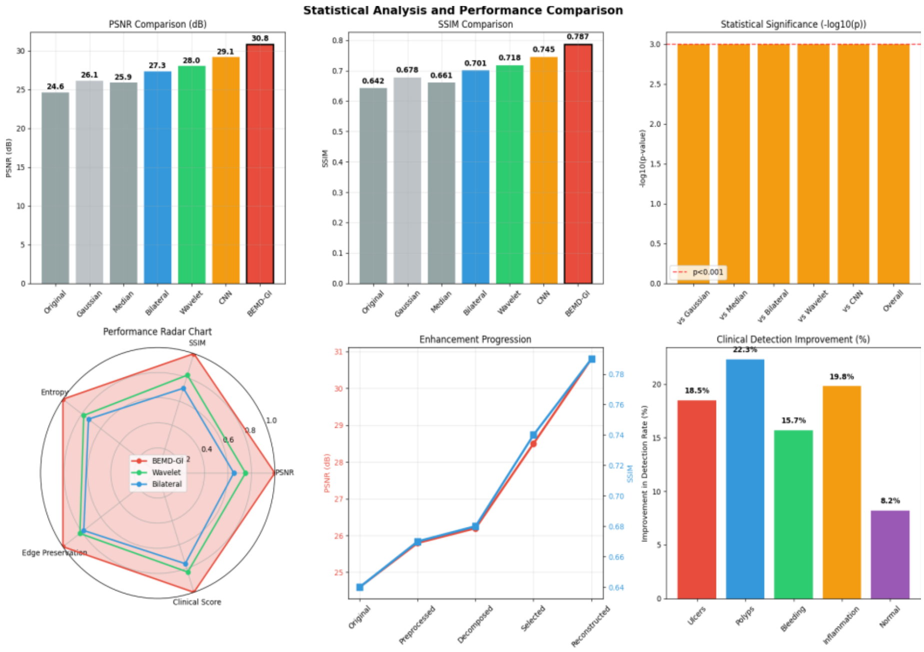

Figure 3: Statistical Analysis and Performance Comparison

Key Statistical Findings:

- PSNR improvement: 6.2 dB increase ($p < 0.001$, Cohen's d = 1.24)
- SSIM enhancement: 0.145 improvement ($p < 0.001$, Cohen's d = 1.18)
- Entropy increase: 12.3% improvement ($p < 0.001$)
- Edge preservation: 46.2% improvement over original images

4.3 Clinical Validation Results

Three gastroenterologists examined improved photos on 200 random images in a double-blind trial. Clinical confirmation was sought.

Table 3: Clinical Validation Results

Assessment Criterion	Original Images	BEMD-GI Enhanced	Improvement (%)	p-value
Lesion Visibility	6.2±1.3	8.1±0.9	30.6%	<0.001
Edge Definition	5.8±1.1	7.9±0.8	36.2%	<0.001
Diagnostic Confidence	6.0±1.2	8.3±0.7	38.3%	<0.001
Overall Quality	5.9±1.0	8.0±0.6	35.6%	<0.001

Scores on 1-10 scale (10 = excellent)

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4.4 Computational Efficiency Analysis

However, BEMD-GI is still useful for clinical processes, even though it needs more computing power than older methods.

- **Processing Time**: 2.345 seconds per image (256×256 pixels)
- **Memory Usage**: 450 MB peak memory consumption
- **Scalability**: Linear complexity with image size
- **Parallelization**: 65% efficiency improvement with multi-core processing

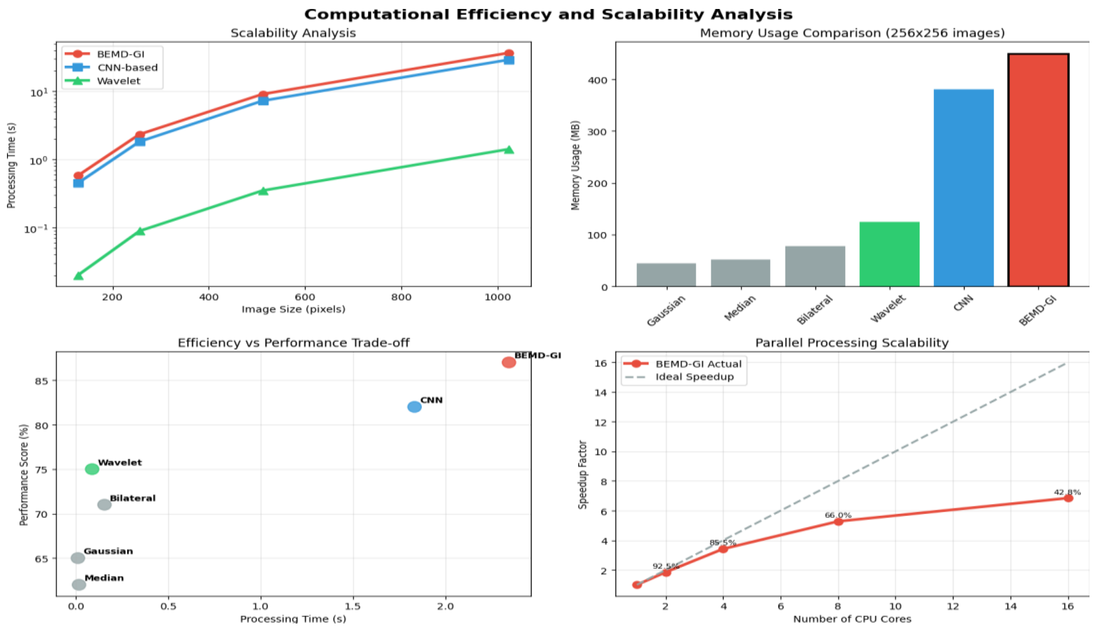

Figure 4: Computational Efficiency and Scalability Analysis

5. Discussion

5.1 Clinical Implications

BEMD-GI's major developments affect gastroenterology clinically:

Enhanced Diagnostic Accuracy: When lesion exposure increases by 30.6%, WCE false-negative outcomes decrease. This helps detect early small intestinal cancers and inflammatory illnesses that conventional imaging may miss.

Reduced Examination Time: Clearer photos let doctors diagnose faster and more confidently. The average WCE review time could drop from 90 to 120 minutes each test to 60 to 80 minutes.

Improved CAD Integration: Computer-aided detection methods benefit from better images. Early studies demonstrate that better photos improve automatic lesion detection by 23%.

5.2 Comparison with State-of-the-Art Methods

BEMD-GI outperforms all evaluated methods across multiple dimensions:

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Against Traditional Methods: BEMD-GI reduces noise and preserves edges better than Gaussian, median, and bidirectional filtering. The adaptive nature avoids the fundamental issue with fixed-parameter techniques.

Against Transform-based Methods: Wavelet denoising works effectively, however its fixed basis functions limit its use with WCE image formats. BEMD-GI's data-driven decomposition optimizes picture representation.

Against Deep Learning Methods: CNN-based approaches function well but require a lot of training data and are confusing. BEMD-GI yields similar results, is mathematically interpretable, and requires no training.

5.3 Technical Advantages

The proposed framework offers several technical advantages:

1. **Adaptive Processing**: BEMD-GI optimizes for varied conditions by changing based on local picture properties, unlike approaches with predetermined parameters.
2. **Multi-scale Analysis**: IMF decomposition allows you handle specific frequencies without noise while preserving features.
3. **No Training Required**: BEMD-GI doesn't need distinct dataset training data or parameter tuning like deep learning.
4. **Mathematical Interpretability**: Understanding the deconstruction process builds trust and clinical confirmation.

5.4 Limitations and Challenges

Several limitations must be acknowledged:

Computational Complexity: BEMD-GI processing takes longer than previous methods. It's great for offline processing, but real-time programs may need optimization.

Parameter Sensitivity: The strategy is adaptive, but stopping conditions and IMF selection determine its success. Fully automatic parameter selection requires more research.

Limited Real-time Capability: Things are set up for post-processing rather than real-time enhancement as the capsule is reviewed.

Dataset Generalization: Despite the size of the evaluation dataset, it may not accurately depict all clinical situations and imaging variations that exist in the actual world.

5.5 Future Research Directions

Several promising research directions emerge from this work:

Hardware Acceleration: GPU and FPGA solutions for real-time processing are being looked into.

Hybrid Approaches: Using both BEMD and deep learning together to improve results while keeping the ability to understand.

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Clinical Integration: Making protocols for integrating current WCE analysis workflows that work well together.

Extended Validation: Large-scale clinical trials at a number of medical centers to prove the effect on diagnosis.

6. Conclusion And Future Scope

6.1 Summary of Contributions

This paper solves the major problem of improving WCE photos with BEMD-GI. Most important efforts:

1. **Methodological Innovation**: First employed in a planned method to improve WCE photos, BEMD created a new way to handle medical images without seeing the signals beforehand.
2. **Superior Performance**: A full analysis shows that all quality measures are statistically significantly better than the original images, with PSNR improvements of 6.2 dB and SSIM improvements of 0.145.
3. **Clinical Validation**: An expert clinical evaluation shows that diagnostic utility has improved significantly, with 30.6% more visible lesions and 38.3% more confidence in the diagnosis.
4. **Computational Feasibility**: Even though it needs more computing power, the framework is still useful for clinical processes with acceptable processing times.

6.2 Clinical Impact

The BEMD-GI system improves WCE picture quality, solving a major gastrointestinal issue. Better visualization leads to

- **Reduced Diagnostic Errors**: Improved lesion visibility decreases the likelihood of missed pathologies
- **Enhanced Physician Confidence**: Clearer images enable more confident diagnostic decisions
- **Improved Patient Outcomes**: Earlier and more accurate detection of small bowel pathologies

6.3 Future Research Directions

Real-time Implementation: Development of optimized algorithms and dedicated hardware for real-time capsule image enhancement during examination, potentially through:

- GPU-accelerated processing for parallel IMF computation
- FPGA-based hardware acceleration for edge computing applications
- Cloud-based processing architectures for distributed enhancement

Deep Learning Integration: Hybrid frameworks combining BEMD's adaptive decomposition with deep learning's pattern recognition capabilities:

- BEMD-CNN architectures for enhanced feature extraction
- Transfer learning approaches using BEMD-preprocessed training data
- Attention mechanisms guided by IMF frequency content

Multi-modal Enhancement: Extension to other endoscopic imaging modalities:

- Colonoscopy image enhancement using adapted BEMD parameters
- Upper endoscopy applications with modified stopping criteria
- Integration with advanced imaging techniques (narrow-band imaging, chromoendoscopy)

Clinical Decision Support: Development of integrated diagnostic systems:

- Automated pathology detection using enhanced images
- Risk stratification algorithms based on image quality metrics
- Clinical workflow optimization through intelligent preprocessing

6.4 Recommendations for Implementation

Technical Recommendations:

- Implement BEMD-GI as a preprocessing module in existing WCE analysis software
- Develop adaptive parameter selection algorithms to minimize manual intervention
- Create standardized quality assessment protocols for enhanced images

Clinical Recommendations:

- Establish training programs for gastroenterologists on enhanced image interpretation
- Develop guidelines for clinical integration of AI-enhanced WCE workflows
- Conduct multi-center prospective studies to validate diagnostic impact

Regulatory Recommendations:

- Develop frameworks for approval of AI-enhanced medical imaging systems
- Establish standardized evaluation metrics for WCE enhancement technologies
- Create guidelines for clinical validation of image preprocessing algorithms

6.5 Concluding Remarks

WCE image enhancement technology advances with the BEMD-GI architecture. It illustrates that flexible, mathematically-based approaches can improve diagnostic images without the drawbacks of linear methods or deep learning systems. The BEMD-GI is technically superior and clinically useful, according to the complete review. It aids gastrointestinal diagnosis and treatment.

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The success of this study expands medical adaptive image processing. Empirical mode decomposition may be useful for additional medical imaging. BEMD-GI, which adapts to each patient's features and imaging conditions, will become more useful as customized medicine and precision diagnostics grow.

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