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# Real-Time Self-Supervised Ultrasound Image Enhancement Using Test-Time Adaptation for Sophisticated Rotator Cuff Tear Diagnosis

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## Introduction and Background

Ultrasound imaging is widely used in clinical diagnostics due to its affordability, safety, and real-time capability; however, its intrinsic low resolution and speckle artifacts limit diagnostic reliability, particularly for computer-aided diagnosis (CAD). Supervised learning methods for ultrasound image enhancement are restricted by the impracticality of acquiring paired clean and degraded images, while existing self-supervised or zero-shot approaches suffer from slow inference, hindering real-time clinical deployment. To address these constraints, this study proposes a real-time self-supervised enhancement framework using test-time adaptation (TTA) to improve both image quality and rotator cuff tear (RCT) diagnostic performance.

## Material and Method

An ultrasound dataset of 20 patients with pixel-level RCT annotations was collected under IRB approval. The proposed framework consists of two stages: (1) pretraining on external natural-image data (STL-10) using synthetic degradations and MSE-based restoration, and (2) test-time adaptation during inference using perceptual VGG-feature loss to refine enhancement on real ultrasound input. A lightweight CNN with NAF blocks enables efficient computation. Image-quality metrics included contrast-to-noise ratio (CNR), generalized CNR (gCNR), and NIQE-K. Segmentation performance was assessed using SAM2 to quantify the effect of enhancement on RCT delineation.

## Results

Three TTA iterations yielded the optimal balance between performance and speed. Compared with zero-shot and self-supervised baselines (ZSSR, DIP), the proposed method achieved the highest CNR, gCNR, and lowest NIQE-K, demonstrating superior enhancement quality. Segmentation accuracy improved by 13.4%, while overall image-quality improvement reached up to 18%. Importantly, the method achieved real-time performance (≈5 FPS, <1 s inference) with fewer parameters than competing models.

## Conclusions

This study presents a real-time self-supervised ultrasound enhancement framework that effectively improves both image quality and RCT segmentation performance without requiring paired training data. By combining domain-agnostic pretraining with test-time adaptation, the method enables clinically feasible, rapid enhancement suitable for integration into ultrasound imaging workflows.


Figure & Table 1.

TABLE I
QUANTITATIVE COMPARISONS OF DIFFERENT ADAPTATION ITERATIONS IN OUR TEST-TIME ADAPTATION FRAMEWORK IN TERMS OF CNR, GCNR, NIQE-K, AND INFERENCE TIME ON THE RCT ULTRASOUND IMAGES

| # of adaptation iteration | CNR | gCNR | NIQE-K | Inference time (ms) |
|---|---|---|---|---|
| three | **1.2521** | **0.7763** | 0.5824 | **218.81** |
| five | 1.2488 | 0.7618 | 0.5820 | 363.24 |
| seven | 1.2386 | 0.7479 | 0.5815 | 511.37 |
| ten | 1.2187 | 0.7332 | **0.5811** | 727.40 |

The best performance is in bold.

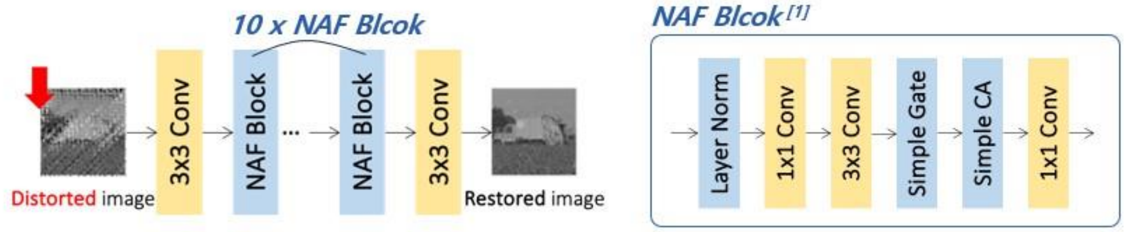
TABLE II
QUANTITATIVE COMPARISONS OF OUR APPROACH WITH OTHER METHODS IN TERMS OF CNR, GCNR, NIQE-K, RCT SEGMENTATION PERFORMANCE, INFERENCE TIME, AND THE NUMBER OF PARAMETERS ON THE RCT ULTRASOUND IMAGES

| Methods | Original | ZSSR | DIP | Ours-3 |
|---|---|---|---|---|
| CNR | 1.061 | 0.9446 | 1.1196 | **1.2521** |
| gCNR | 0.6781 | 0.6374 | 0.6667 | **0.7763** |
| NIQE-K | 0.5833 | 0.5831 | 0.5838 | **0.5824** |
| RCT Segmentation | 0.2666 | 0.1949 | 0.2448 | **0.3022** |
| Inference time (s) | - | 6.917 | 11.561 | **0.219** |
| # of parameters (MB) | - | 0.850 | 7.500 | **0.056** |

The best performance is in bold.

Figure & Table 2.

- **Network Architecture and Training Strategy**
  - **Pre-training**




- **Optimization settings**
  - ✓ ADAM optimizer
  - ✓ Number of epochs: 100
  - ✓ Learning rate : 1e-4
  - ✓ Loss function : Mean Squared Error (L2)
- **Dataset**
  - ✓ STL-10 Dataset (Natural images, Classification-specific dataset)
  - ✓ Distortions :
    - Random downsampling
    - Gaussian noise
    - Gaussian blurring


[1] Chen, Liangyu, et al. "Simple baselines for image restoration." *European conference on computer vision*. Cham: Springer Nature Switzerland, 2022.