Ultrasound Image Restoration Using Weighted Nuclear Norm Minimization

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INTRODUCTION

Ultrasound images have been widely used in clinical examination and diagnosis, owing to its advantages of low cost, real time, safety. The system imaging mechanism is based on the echo information of ultrasonic waves to obtain the real-time state of body tissues. However, multiplicative speckle noise often occurs in ultrasound images because of wave interference, which reduces the image quality and brings difficulties to the diagnose and subsequent applications. In order to preserve more details and texture, we investigates a nonconvex low-rank medical ultrasound image despeckling model based on the weighted nuclear norm minimization (WNNM) and data fidelity term. This optimization problem can effectively solved by alternating direction method of multipliers (ADMM). The experimental results on simulated images and real medical ultrasound images demonstrate the excellent performance of the proposed method compared with other four state-of-the-art methods.

THE PROPOSED METHOD

- Based on nonlocal self-similarity and low-rank and statistics priors of ultrasound image, we propose a WNNM-based despeckling model. The pipeline is illustrated in Fig. 1.
- Concretely, the ultrasound image is divided into nonlocal similar patch matrices, which are denoised respectively. The restored ultrasound image can be reconstructed by aggregating all restored pathes.
- The proposed model can be formulated as:

\[
\min_X \left\{ \frac{1}{2} \| X - Y \|_F^2 + \lambda \| X \|_{	ext{nuc}} \right\}
\]

where \( X \) denotes the original image patch, and \( Y \) represents the observed image patch.

- The optimization problem is solved by ADMM. The aggregated Lagrangian function is formulated as:

\[
\mathcal{L}(X, L, Z) = \left( \frac{1}{2} \| X - Y \|_F^2 + \frac{1}{2} \| X \|_{	ext{nuc}} + \frac{1}{2} \| Z - X \|_F^2 \right)
\]

It is addressed by alternatively optimizing one variable while fixing others.

1. Update subproblem \( X \) via optimizing:

\[
X^{t+1} = \arg \min_X \left\{ \frac{1}{2} \| X - Y \|_F^2 + \frac{\mu}{2} \| X - X^{t} - L^t \|_F^2 \right\}
\]

2. Update subproblem \( L \) via optimizing:

\[
L^{t+1} = \arg \min_L \left\{ \frac{\mu}{2} \| X^{t+1} - L^{t+1} \|_F^2 \right\}
\]

3. Update Lagrange multiplier \( Z \) via:

\[
Z^{t+1} = Z^t + \mu (X^{t+1} - L^{t+1})
\]

4. Update parameter \( \mu \) via:

\[
\mu^{t+1} = \rho \mu^t
\]

EXPERIMENTAL RESULTS

Experimental environment:

- Compared methods: JY, SRAD, NLLRF, DFoE, NNM-US.
- Evaluation criteria: SNR, PSNR, SSIM.