Program Digest, 2019 IEEE International Ultrasonics Symposium (IUS)
Glasgow, Scotland, October 6-9, 2019

Simultaneous Compression and De-Speckling of Medical Ultrasound Images

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***Abstract*—Compression of medical ultrasound images is necessary in order to meet storage and transmission requirements. Moreover, de-speckling is essential for diagnostic applications. We propose an algorithm for simultaneous compression and de-speckling of ultrasound images, based on optimization of quantization parameters applied on the coefficients of the coding transform. The optimization is applied in the rate-fidelity space, such that for a given target compression ratio, an optimal fidelity is obtained with respect to an a-priori known de-speckled image. The algorithm was tested on a set of fetal images. Results show that the reconstructed images better resemble the de-speckled images, compared to those obtained using standard quantization.**

Keywords—Image compression, quantization, de-speckling, fidelity, fetal ultrasound images.

I. Introduction

The ever growing use of medical ultrasound images for diagnostics poses challenges in terms of storage, transmission, processing and image enhancement [1]. Image quality in ultrasound B-mode has significantly improved during the last years, however, images are inherently noised with granular-patterned speckle noise, which is produced by interfering echoes backscattered from the object heterogeneities. Speckle noise impairs the image contrast and obscures image details, and interferes with CAD (computer aided detection), image segmentation and registration [2].

A variety of methods for image de-speckling have been studied in recent years [3]. Recently, non-local patch and Bayesian-based algorithms, namely the Non-Local-Means method (NLM) have been proposed for speckle reduction [4]. These algorithms yield improved results in terms of speckle de-noising and edge preservation. Furthermore, previous techniques for ultrasound image compression have been suggested [5,6], and it was demonstrated that compression ratios of 20:1 to 40:1 are attainable with fair image quality.

We propose a method that yields compressed images, whilst effectively reducing speckles and preserving the edges. The proposed method enables to operate under the constraint of a given target bit-rate. Our algorithm is based on a rate-fidelity optimization of the quantization parameters in Wavelet transform coding. The fidelity of the reconstructed image is measured with respect to an a-priori known *de-speckled* image. This a-priori image may be obtained by applying any previously tested de-speckling algorithm; in this work, we demonstrate the method for the case where the de-speckling is applied using the NLM method.

II. Methods

The optimization algorithm used in this work is based on the scheme proposed in [7], where a fidelity measure of the decoded (de-compressed) image with respect to the a-priori de-speckled image is maximized for the given target bit-rate.

A. Fidelity Measure

We propose a fidelity measure that is a combination of the SSIM (Structural Similarity) and EP (Edge Preserve) measures. The well-known SSIM is a metric that is considered to reflect the similarity between two images, as perceived by the human visual system [8]. Previous work has shown that SSIM is more sensitive than Peak-Signal-to-Noise-Ration (PSNR) to degradations resulting from transform-based compression [9].

Regarding the EP metric, it is a measure of the ability of the speckle reduction method to preserve edges in the image [10]. It is defined as:

$$EP(f,\hat{f}) = \frac{\Gamma\left(\Delta S_f-\overline{\Delta S_f},\Delta S_{\hat{f}}-\overline{\Delta S_{\hat{f}}}\right)}{\sqrt{\Gamma\left(\Delta S_f-\overline{\Delta S_f},\Delta S_f-\overline{\Delta S_f}\right)\cdot\Gamma\left(\Delta S_{\hat{f}}-\overline{\Delta S_{\hat{f}}},\Delta S_{\hat{f}}-\overline{\Delta S_{\hat{f}}}\right)}} \tag{1}$$

where ΔS_f , $\Delta S_{\hat{f}}$ are the approximations of the Laplacian operator on the original and filtered images, respectively, and the inner product $\Gamma(\cdot,\cdot)$ is defined as

$$\Gamma(t_1,t_2) \triangleq \sum_{(i,j)\in Im} t_1(i,j)\cdot t_2(i,j) \tag{2}$$

where i,j is the pixel's position in the image. $\overline{\Delta S_f}$, $\overline{\Delta S_{\hat{f}}}$ are the mean values of ΔS_f, $\Delta S_{\hat{f}}$, respectively, calculated over the entire images. The closer the EP measure is to 1, the better is the ability of the de-speckling method to preserve the image edges.

We define the Fidelity Index (FI) for our optimization as:

$$FI = SSIM(\hat{f},f_{SR}) + \lambda EP(\hat{f},f) \tag{3}$$

where f , f_{SR} , $\hat{f}$ are the original, speckled reduced and reconstructed images, respectively; and λ is a positive constant. As discussed above, the speckle suppressed image f_{SR} may be obtained using any de-speckling algorithm. In this work, we chose to apply the NLM method.

B. Proposed Algorithm

The basic idea of the optimization algorithm is to start with an initial quantization vector, which corresponds to a certain point in the rate-fidelity domain. Then, for each iteration, one entry of the vector is updated such that the ratio between the

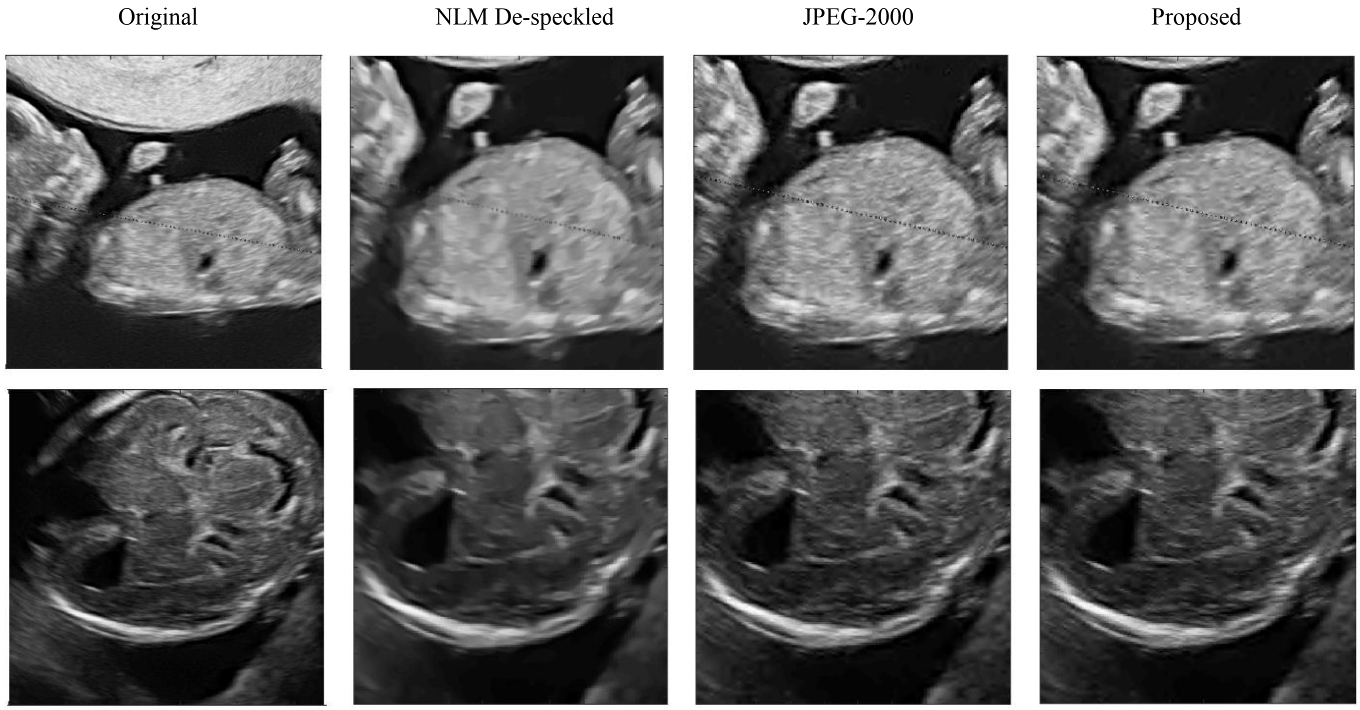

Figure 1 – From left to right: Original fetal image, NLM de-speckled, reconstructed after JPEG-2000 coding, and reconstructed after proposed method. Top row – Fetal #1; Bottom row – Fetal #2.

increase (decrease) in FI to the decrease (increase) in the compression ratio (CR) is maximized (minimized). This FI-CR ratio is actually the slope in the rate-fidelity domain. The algorithm converges when the target compression ratio is reached.

We summarize the steps of the algorithm:

Input: Target compression ratio, denoted CR_{trgt}.
Source (input) image f_{src}, to be optimally coded.
Target image f_{trgt} (f_{trgt} is the de-speckled version of f_{src}).
Quantization multiplicative update step $s > 1$.

Output: Quantization vector q.

Step 1: Initialize the $3N_L + 1$ entries of quantization vector q (N_L is the number of Wavelet decomposition levels).

Step 2: Calculate the compression ratio and the reconstructed image $\hat{f}$ using the current vector q, and denote it by CR_{curr}.

Step 3: Calculate the current fidelity index:

$$FI_{curr} = SSIM(\hat{f}, f_{trgt}) + \lambda EP(\hat{f}, f_{src}) \tag{4}$$

Step 4.1: If $CR_{curr} \leq CR_{trgt}$, then for each $i = 1, \dots, 3N_L + 1$, define:

$$\Delta_i FI \triangleq FI_{i,next} - FI_{curr} \tag{5a}$$

and

$$\Delta_i CR \triangleq CR_{i,next} - CR_{curr} \tag{5b}$$

where $FI_{i,next}$, $CR_{i,next}$ are the fidelity index and compression ratio, respectively, obtained when the i-th entry in the vector, $q(i)$, is replaced with $s \cdot q(i)$.

Then, find the index i_{max} which satisfies:

$$i_{max} = Arg \max_i \left\{\frac{\Delta_i FI}{\Delta_i CR}\right\} \tag{6}$$

and update the table's i_{max}-th entry according to

$$q(i_{max}) \to s \cdot q(i_{max}) \tag{7}$$

Step 4.2: If $CR_{curr} \geq CR_{target}$, then for each $i = 1, \dots, N_L + 1$, define:

$$\Delta_i FI \triangleq FI_{i,next} - FI_{curr} \tag{8a}$$

and

$$\Delta_i CR \triangleq CR_{i,next} - CR_{curr} \tag{8b}$$

where $FI_{i,next}$, $CR_{i,next}$ are the fidelity index and compression ratio, respectively, obtained when the i-th entry in the table, $q(i)$, is replaced with $q(i)/s$.

Then, find the index i_{min} which satisfies:

$$i_{min} = \underset{i}{\text{Argmin}} \left\{\frac{\Delta_i FI}{\Delta_i CR}\right\} \tag{9}$$

and update the table i_{min}-th entry according to

$$q(i_{min}) \to q(i_{min})/s. \tag{10}$$

Step 5: Repeat steps 2, 3 and 4 until $|CR_{curr} - CR_{trgt}| < \varepsilon$, where ε is a pre-determined tolerance.

III. Results and Discussion

We tested the proposed method on fetal images. Our algorithm's performance was compared with the JPEG-2000 scheme for the same bit-rate. The performance was evaluated in terms of the SSIM and PSNR metrics of the reconstructed images *with respect to the de-speckled image*.

The results are presented in Fig. 1, where the optimization was applied over the FI as in Eq. (3), with $\lambda = 0.3$. From a qualitative point of view, our method yields de-noised images which are similar to the de-speckled image, while the JPEG-2000 reconstructions better resemble the original image. The resulting fidelity metrics and bit-rates are summarized in

Table 1, where it is shown that our method achieves higher values of fidelity with respect to the de-speckled images.

	Bit-rate (bpp)	SSIM JPEG2000	SSIM Proposed	PSNR JPEG2000 (dB)	PSNR Proposed (dB)
Fetal #1	0.35	0.55	0.58	31.9	32.7
Fetal #2	0.29	0.71	0.73	33.9	35.1

Table 1 - Bit-rates, SSIM and PSNR for fetal images using JPEG-2000 and the proposed method.

IV. Conclusions

In this work an algorithm for simultaneous compression and de-speckling of ultrasound medical images was proposed. The algorithm is based on finding the optimal quantization parameters for Wavelet image coding, such that the reconstructed image best resembles a target de-specked image. Results on real clinical fetal images demonstrate the ability of the method to achieve de-speckled images with bit-rates comparable to existing methods.

Acknowledgment

This work was supported by the Israeli Ministry of Science and Technology and by the Ollendorff Minerva Centre of the Andrew and Erna Viterbi Faculty of Electrical Engineering at the Technion - Israel Institute of Technology. Minerva is funded through the BMBF.

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