MRF DENOISING WITH COMPRESSED SENSING AND ADAPTIVE FILTERINIG

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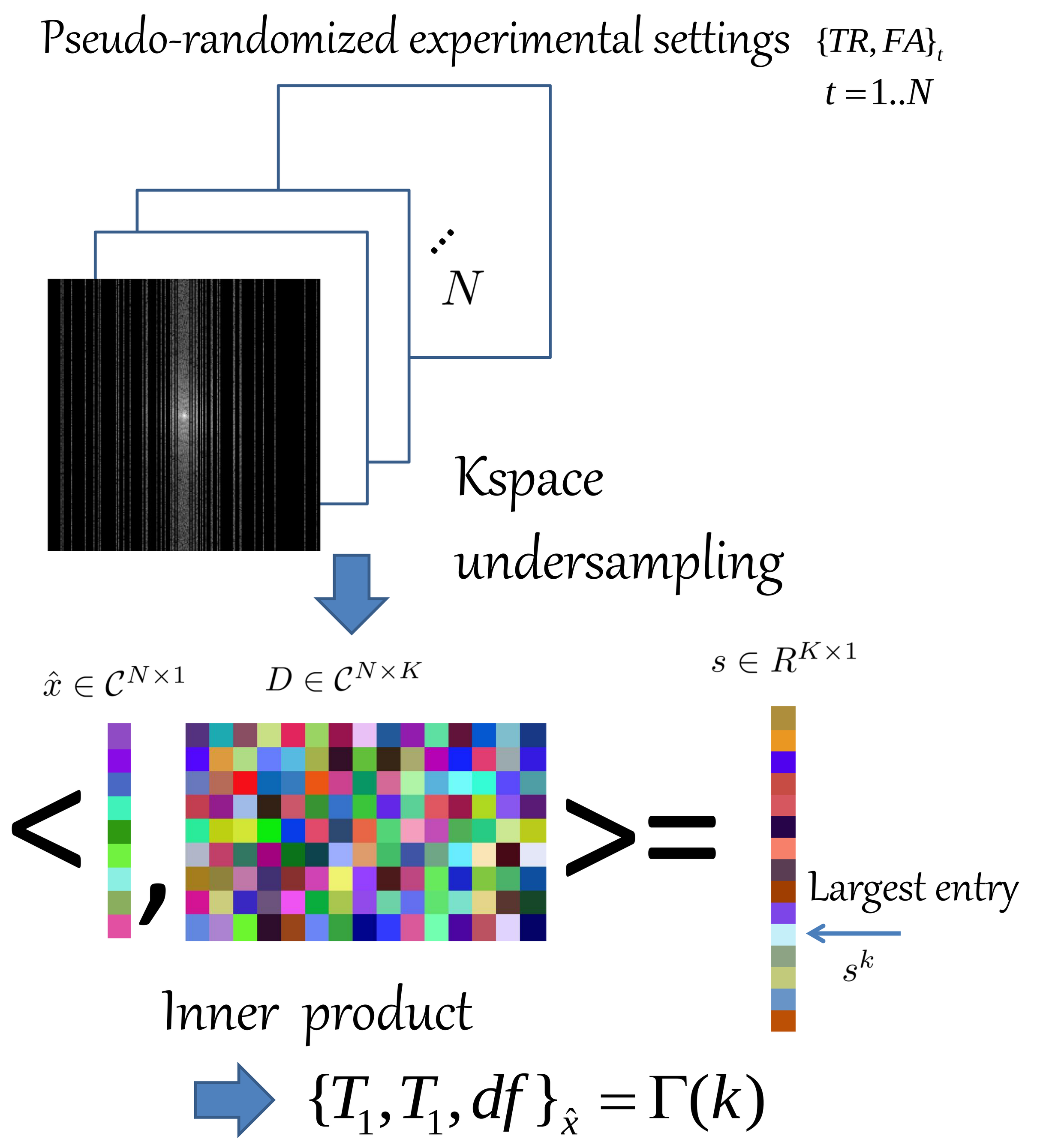
Abstract

The recently proposed **Magnetic Resonance Fingerprinting (MRF)** [1] technique can simultaneously estimate multiple parameters through dictionary matching. It has promising potentials in a wide range of applications. However, MRF introduces errors due to undersampling during the data acquisition process and the limitation of dictionary resolution. In this paper, we investigate the error source of MRF and propose the technologies of improving the quality of MRF with compressed sensing, error prediction by decision trees, and adaptive filtering. Experimental results support our observations and show significant improvement of the proposed technologies.

Introduction and Background

Magnetic Resonance Fingerprinting (MRF) has the potential to quantitatively examine many magnetic resonance parameters simultaneously. The framework is illustrated in the following figure.



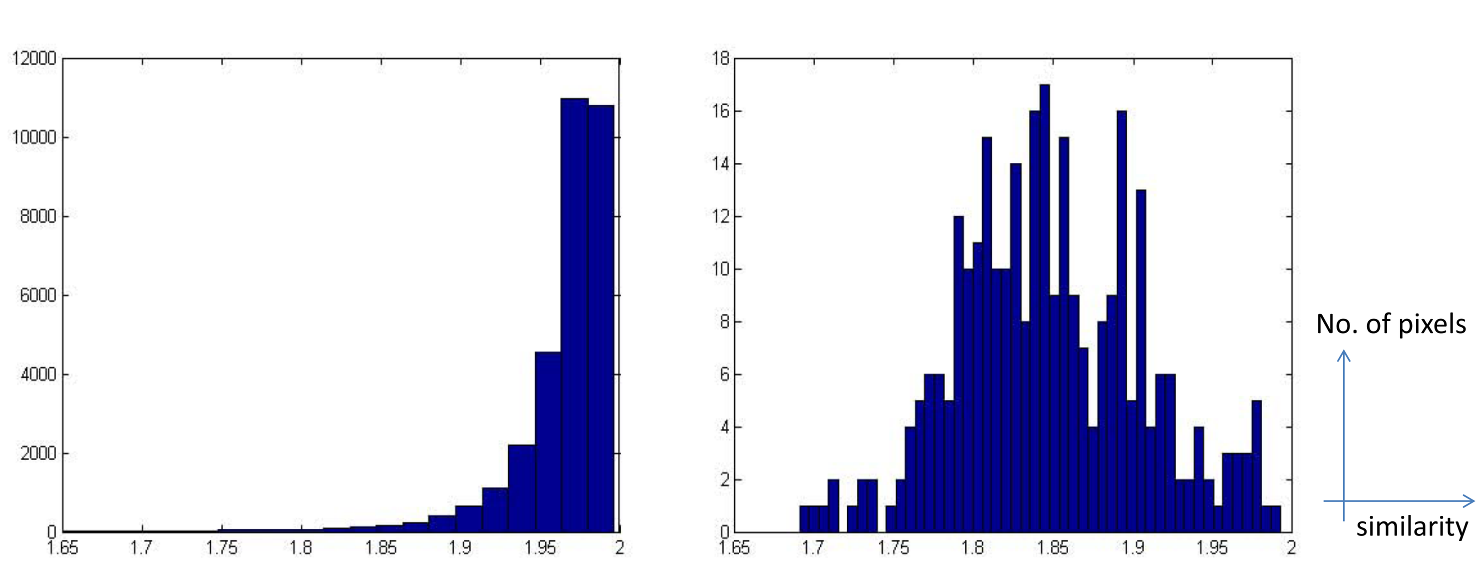
The dictionary is precalculated using the Bloch equation. It includes all possible combinations of parameters given the same set of experimental parameters $\{TR, FA\}_t$. where Γ is the mapping from a dictionary index to the corresponding parameters T_1, T_2 and df.

Our Contribution

We investigated the error sources of MRF and have the following observations.

➢ The aliasing artifacts caused by undersampling can be observed in the estimated parameters maps.

➢ Most errors happen when a true parameter lies between dictionary entries. And the estimated parameter may be far away from the ground truth, which leads to large errors.



Correct pixels　　Incorrect pixels

Histograms of the largest similarities between the signal evolutions and the dictionary.

➢ Compressed Sensing (CS) [2] is applied to reconstruct all the k-space data at each sampling time point before the matching process.

➢ The correctness of every pixel on each parameter map is predicted by a separately trained decision tree[3]. The prediction is based on the largest matching similarities and corresponding indices among all the dictionary entries.

➢ If a pixel is predicted as error, it is replaced with the result of convolving its neighbor pixels with an adaptive filter.

The adaptive filter is defined as:

$$I_{filtered}(p) = \frac{1}{W}\sum_{j\in\Omega/p} w_{p_j} I_{p_j} \qquad (1)$$

$$w_{p_j} = \exp\left(-\frac{\|p-p_j\|_2^2}{\sigma_d^2}\right)\exp\left(-\frac{\|2-s_{p_j}\|_2^2}{\sigma_s^2}\right) \qquad (2)$$

The center pixel p is excluded in Eq. (1) because it may have large error. I_{p_j} is the estimated parameter at neighbor pixel p_j. W is a normalization factor. s_{p_j} is the largest similarity of dictionary matching at pixel p_j.

Simulation Results

➢ Based on an IR-bSSFP sequence using a pseudorandomized series of flip angles and repetition time.

➢ One set of T1, T2 and off-resonance frequency maps are used for training decision trees.

➢ Another two sets of maps are simulated for test.

Our proposed approach (CS-Tree8AF) has the best performance under both measurements and significantly improve the quality of parameter maps estimated with MRF.

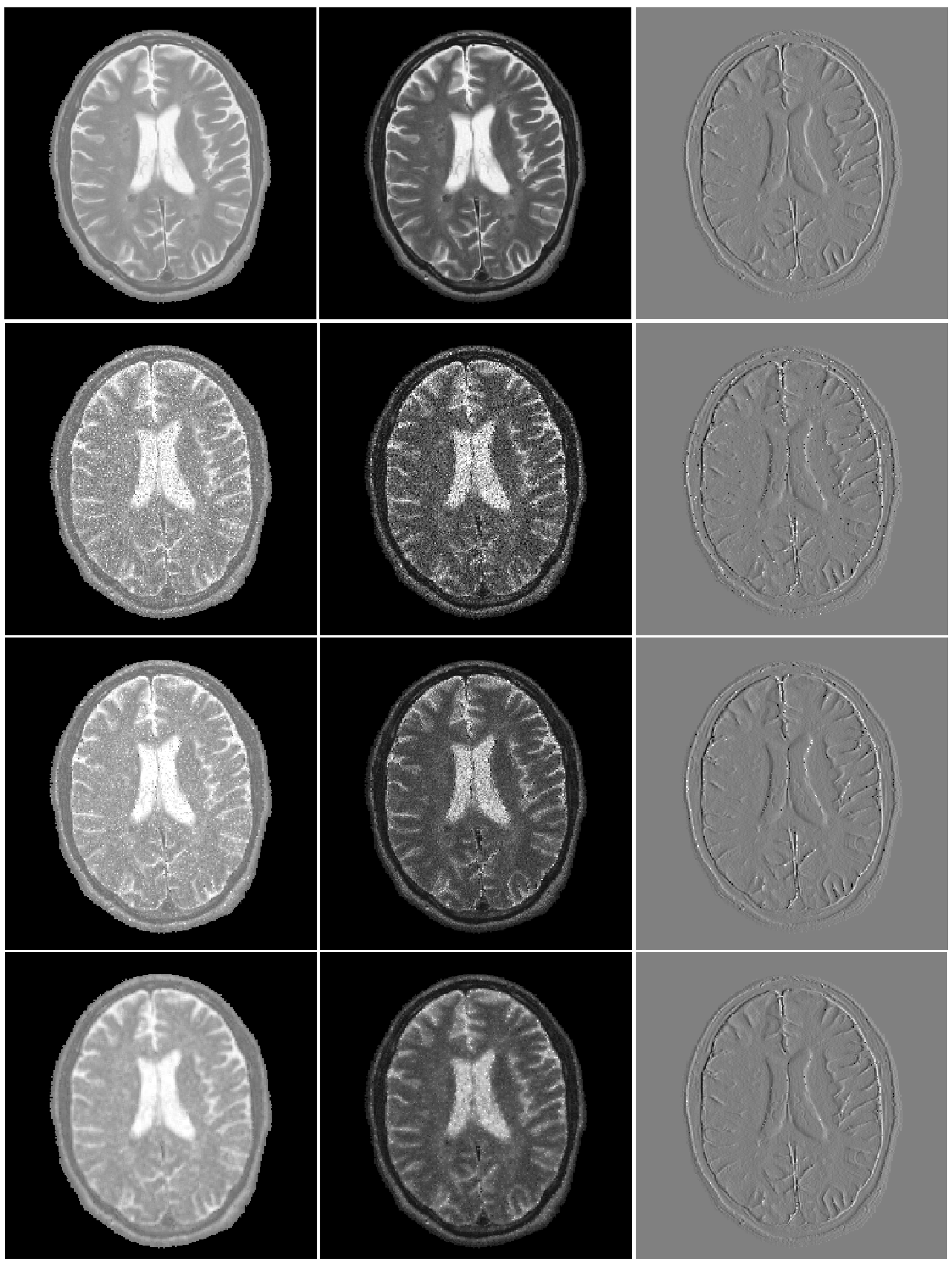
	T1	T2	Off resonance
MRF	24.3\0.731	20.4\0.706	22.9\0.867
CS+MRF	26.2\0.801	21.5\0.802	26.4\0.961
CS-Tree8AF	28.4\0.881	22.9\0.863	28.9\0.974

Quantitative Evaluation of the proposed algorithms
Left\Right: PSNR(dB)\SSIM

➢ MRF: The method in the [1].

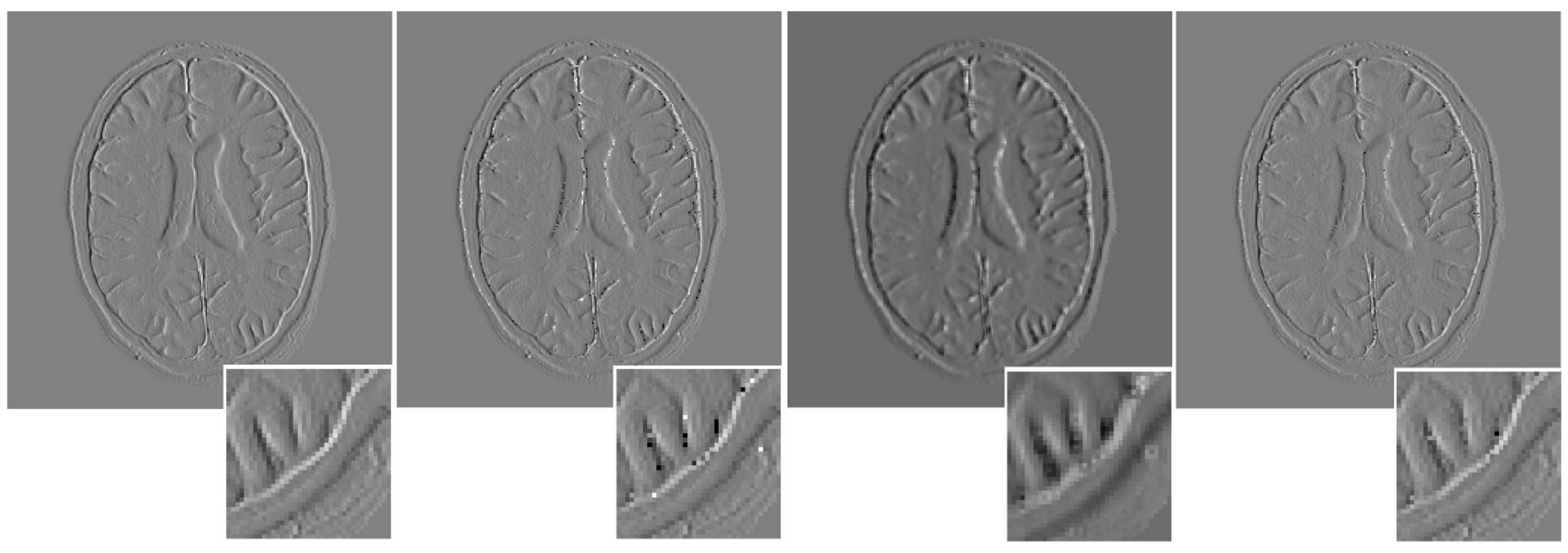
➢ CS+MRF: The kspace data is reconstructed by Compressed Sensing before the dictionary matching process.

➢ CS-Tree8AF: Our proposed method.



T1 map　　T2 map　　off-resonance frequency map

From top to bottom: ground truth, MRF, CS+MRF and CS-Tree8AF.



Ground truth　　CS+MRF　　CS+MRF with Gaussian filtering　　CS+MRF with Adaptive filtering

Reference

[1] Dan Ma, Vikas Gulani, Nicole Seiberlich, Kecheng Liu, Jeffrey L Sunshine, Jeffrey L Duerk, and Mark A Griswold, "Magnetic resonance fingerprinting," Nature, vol. 495, no. 7440, pp. 187–192, 2013.

[2] Michael Lustig, David Donoho, and John M Pauly, "Sparse mri: The application of compressed sensing for rapid mr imaging," Magnetic resonance in medicine, vol. 58, no. 6, pp. 1182–1195, 2007.

[3] J. Ross Quinlan, "Induction of decision trees," Machine learning, vol. 1, no. 1, pp. 81–106, 1986.

[4] Zhou Wang, Alan C Bovik, Hamid R Sheikh, and Eero P Simoncelli, "Image quality assessment: From error visibility to structural similarity," Image Processing, IEEE Transactions on, vol. 13, no. 4, pp. 600–612, 2004.