TABLE I
PSNR (dB) RESULTS FOR IMAGE CORRUPTED BY GAUSSIAN AND IMPULSE NOISE

Filter Type	Image		
	Lenna	Home	Harbor
Median (3x3)	31.36	26.67	24.65
Bidirectional multistage median (5x5)	31.58	28.73	28.02
WM1	31.58	28.87	27.84
WM2	29.85	27.92	27.71
WM3	32.00	28.08	26.29
Spline filter	32.96	31.89	31.54

s. It should be noted, however, that the code of the proposed method and the other methods has not been optimized.

The convergence of the proposed method has been studied experimentally. The algorithm converged for each block of data in the sliding window during the image restoration.

V. CONCLUSION

A new image approximation scheme is proposed. The structural constraints are incorporated in an iterative M-estimator algorithm. As a result, an image modeling method is obtained that is not influenced by outliers and reduces Gaussian and heavy-tailed noise efficiently; and, at the same time it retains important details. The images are modeled as tensor product bicubic B-splines. The smoothing parameter λ is estimated separately for each processing window, thus allowing it to adapt to local structures of the image. As a result, one can expect excellent Gaussian noise removal in smooth and slowly varying areas where λ is large and at the same time very good preservation of important details (small values of λ). Results obtained by applying the filter based on the presented approximation algorithm to real scenes indicate that this method is robust with respect to variations in the statistics of both the noise and the image.

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On "The Convergence of Mean Field Procedures for MRF's"

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In [1], Zhang attempts to establish convergence of a mean-field iteration for an Ising Markov random field (MRF) for large values of the hyperparameter β. Unfortunately, (16b), which states

$$|T_\delta(u_1) - T_\delta(u_2)| \leq |u_1 - u_2|$$

is not correct for the function $T_\delta(u)$ defined in (15) and Fig. 2. In fact, any function that satisfies (16b) for all u_1 and u_2 is necessarily a continuous function, unlike the particular $T_\delta(u)$ defined in (15).

Thus, the convergence of the mean field iteration remains an important open question for large β.

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