Recently, several denoising methods have been proposed to remove unknown noise from images [16, 17, 19, 20, 18, 14]. Among them, the “Noise Clinic” [19, 20] estimates the noise distribution by using a multivariate Gaussian model and removes the noise by using a generalized version of nonlocal Bayesian model [24]. Zhu et al. proposed a Bayesian method [18] to approximate and remove the noise via a low-rank mixture of Gaussians (MoG) model. There are also several methods specifically designed for real noisy image denoising [14, 21]. The method in [14] models the cross-channel noise in real noisy image as a multivariate Gaussian and the noise is removed by Bayesian nonlocal means. The commercial software Neat Image [21] estimates the noise parameters from a flat region of the given noisy image and filtered the noise correspondingly. Almost all the methods mentioned above [16, 17, 19, 20, 18, 14] use Gaussian or MoG to model the noise in real noisy images. Nonetheless, the noise in real noisy images is very complex and hard to be modeled by explicit distributions.

The noise in real-world noisy images is much more complex than additive white Gaussian noise and hard to be modeled by simple analytical distributions such as Gaussian or mixture of Gaussians, making the real noisy image denoising problem very challenging. In this paper, we proposed a simple yet effective solution for real noisy image denoising without explicitly assuming certain noise models. Specifically, we firstly learned image priors from external clean images, and then employed the learned external priors to guide the learning of internal priors from the given noisy image. The learned hybrid priors are utilized for real noisy image denoising. Experiments on two real noisy image datasets, where the images were captured under indoor or outdoor lighting conditions by different types of cameras and camera settings, demonstrated that our proposed method achieved much better performance than state-of-the-art image denoising methods.