(a) Original image (b) Conventional CoSaMP  (c) 2-clusters intensities based CoSaMP  
(d) 5-clusters intensities based CoSaMP  (e) 10-clusters intensities based CoSaMP  (f) 50-clusters intensities based CoSaMP

Fig. 4. (a) The original lunar grey image (resolution: \(128 \times 128\)) with \(S = 1739\) nonzero values. The random Gaussian measurement number of CS over this image is \(M = 3S = 5217\) measurements, which is \(\frac{5217}{128 \times 128} \approx \frac{1}{3}N\). (b) The reconstructed image using conventional CoSaMP recovery method. (c)-(f) The images reconstructed with 2, 5, 10 and 50 clusters of values for intensities CoSaMPs. The computational time is (b) 5.82 seconds (c) 2.94 seconds (d) 3.24 seconds (e) 5.74 seconds and (f) 10.36 seconds

B. More experiments in general

In this subsection, we evaluated our proposed approach on three different images sets: (1) the image set chosen from Caltech 101 database contains five images, sparse in pixel domain; (2) the natural image set contains four images, sparse or compressible in wavelet domain; (3) background subtracted color image set.

For the first image set, since we have concluded in the above section that 10 can be seen as an optimal cluster number of intensities for the images sparse in pixel domain, we set \(K\) of \(K\)-cluster valued CS to be 10. In addition, all the measurement numbers used for compressing these images were chosen to be \(3S\), which is less than the least measurement number \(4S\) required for successful reconstruction in conventional CS \([4]\). Then, the reconstruction results are presented in Figure 6, and these results show the better performance of \(K\)-cluster valued CS for compressing images that are sparse in standard domain.

With the second image set, we have evaluated the promise of the proposed CS approach on compressing the images in wavelet domain. Here, as aforementioned in Section III, we chose