A Frustratingly Hard Way to See How You Look Without Your Glasses*

Assignment 1 | EE698K | Winter Semester'18

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1 Image Inpaiting via Sparse Representation

To illustrate the task of image inpainting using sparse representation [2], the following two images, and corresponding masks, were chosen (Figure 1). The images that were used to create the dictionaries (which have

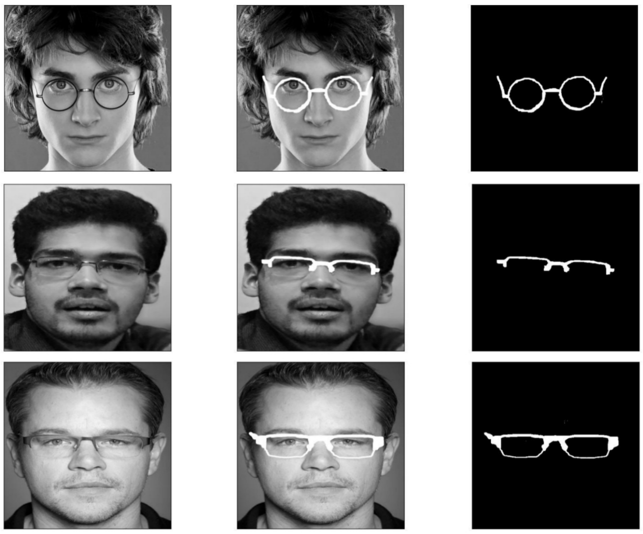


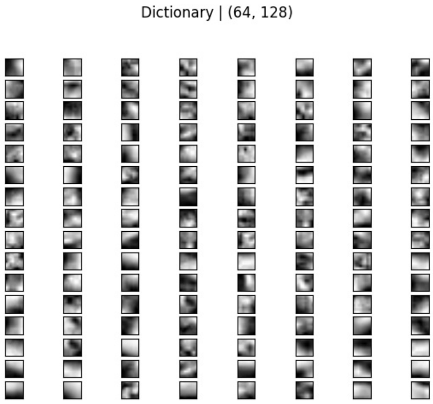
Figure 1: **Left**: The original images (Daniel Radcliffe in Row 1, Gaurav Verma in Row 2, and Matt Damon in Row 4) **Center**: The images with missing glasses. **Right**: The mask that gives the center image, when overlapped with the original image.

been shown in Figure 3) have been shown below, in Figure 2. Please note that at any time, the dictionary was created using six of these images (the five images in the right, along with one of the three images in the left).

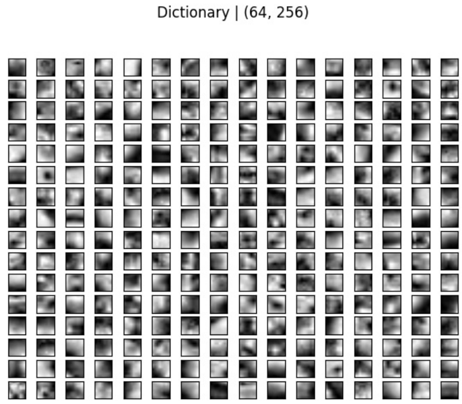
Figure 2: The images that were used to create the dictionaries. The five images on the left were always used, along with an additional image from the left, depending on which test image was being inpainted.

*A simpler way would have been to promote some narcissistic self-indulgence by asking the students to click a selfie without their glasses, but that wouldn't have met the goal of acquainting them with the power of sparse representation. Essentially, the struggle we are in today is developing the strength we will need tomorrow.

The dictionaries that were created using the above images (shown in Figure 2), have been shown below. The first image shows a dictionary of size $(64, 128)$, while the second image shows a dictionary of size $(64, 256)$. Please note that the shown dicitonaries were created using the five images in the right, and Gaurav Verma's image in the left (in Figure 2).



(a) The small dictionary of dimension $(64, 128)$



(b) The large dictionary of dimension $(64, 256)$

Figure 3: The two dictionaries have been shown above. The columns of these dictionaries were reshaped into patches of size $(8, 8)$ to facilitate better representation. These dictionaries were constructed using the images shown in Figure 2.

The $(8, 8)$ patches from the image that was to be inpainted, were filled in a minimum-missing-first order. I.e., in any given iteration, the patch that had the least number of missing pixels (due to the mask) was filled first, followed by the next ones. The following figure illustrates one such $(8, 8)$ patch, filled using (a) orthogonal matching pursuit (OMP) and (b) iteratively reweigthed least square (IRLS) method.

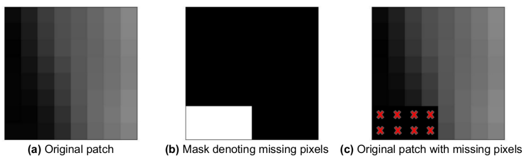
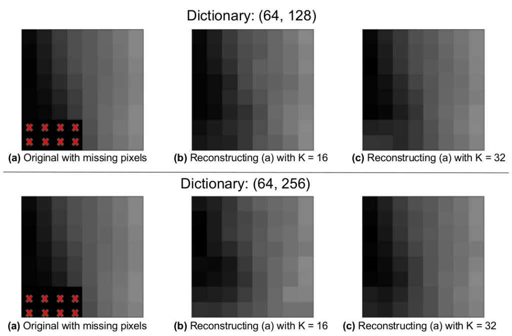
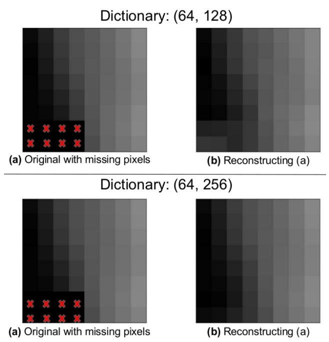


Figure 4: **(a)**: The original patch consisting of 64 pixels. **(b)**: The mask for the patch shown in (a). The white pixels denote that the corresponding pixels in (a) are missing. **(c)**: The original patch, with missing pixels hidden marked by a red cross. Zoom in for better a detailed view.



(a) Orthogonal Matching Pursuit (OMP)



(b) Iteratively Reweighted Least Squares (IRLS)

Figure 5: Reconstruction of a (8×8) patch using OMP and IRLS

The results of the inpainting have been shown in the following figure. The naturalness image quality evaluator (NIQE) has also been mentioned against the inpainted images. To demonstrate the robustness of this method, the results have been shown for four input images.

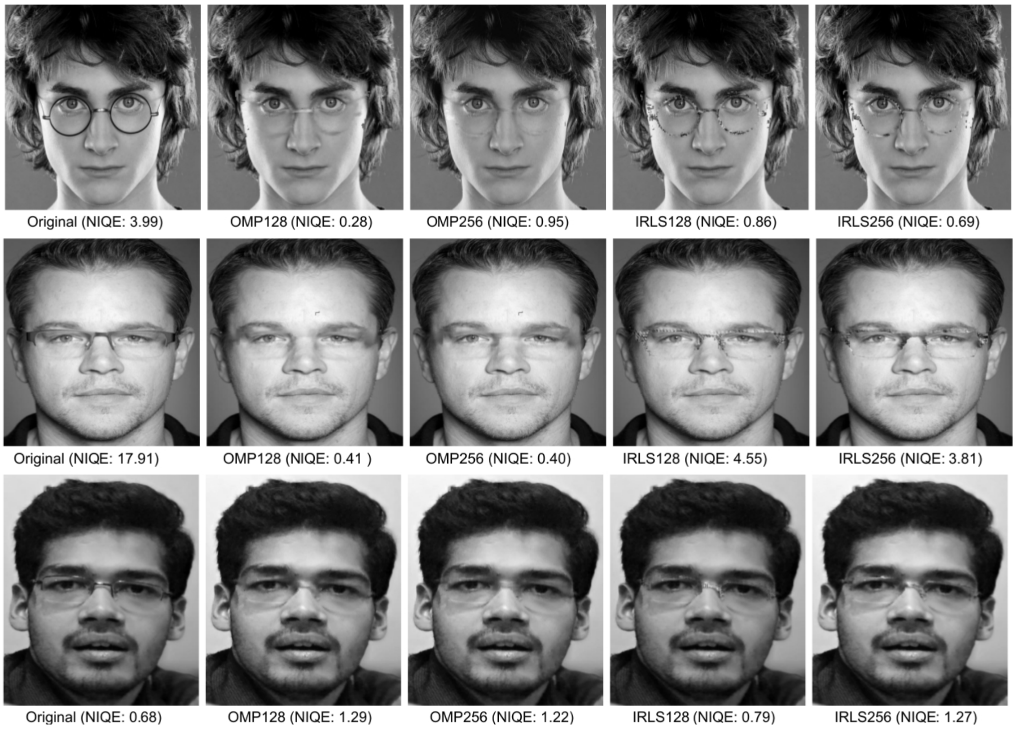


Figure 6: The results for OMP and IRLS have been shown for three input images (Daniel Radcliff in Row 1, Matt Damon in Row 2, and Gaurav Verma in Row 3). The NIQE values for each of the images have been mentioned below them. OMP128 denotes that the inpainting was done using the $(64, 128)$ dimensional dictionary, while OMP256 denotes that the inpainting was carried out using the $(64, 256)$ dimensional dictionary. Similarly convention was used to denote inpainting using IRLS.

The plot depicting the variation of NIQE with sparsity has been shown on the next page (Figure 7) . This plot was obtained by evaluating NIQE index for inpainted images of Daniel Radcliff, using the $(64, 256)$ dimensional dictionary,at different values of sparsity.

2 Observations

Qualitatively speaking, the inpainting using orthogonal matching pursuit (OMP) gives better results than inpainting using iteratively reweigthed least square (IRLS) method. Moreover, as the number of columns are increased (from 128 to 256), the quality of inpainting seems to improve for both the methods. This is can explained using the fact that a dictionary with more columns, gives a larger (and more representative) sample to choose from to represent a given patch. As far as **quantitave** observations are concerned, I believe that the results using NIQE as evaluation index are too inconsistent to comment on the nature of results using the two methods (or using larger dictionaries, for that matter). This can be explained to some extent using this fact: Mittal et al. [1] have tested the performance of NIQE index on five different distortion categories, two of which are compression methods (JPEG2000 and JPEG), additive white Gaussian noise (AWGN), Gaussian blur, and Rayleigh fast fading channel distortion. None of these distortions include the one that we are seeing here. However, a standalone look at the NIQE values suggest the 'naturalness' of inpainted images.

3 Acknowledgements

I would like to thank the Course Instructor, Prof. Tanaya Guha, for giving us the space to think that we can keep our style. I would also like to thank Aditya Vikram and Vikulp Bansal for letting me use their images.

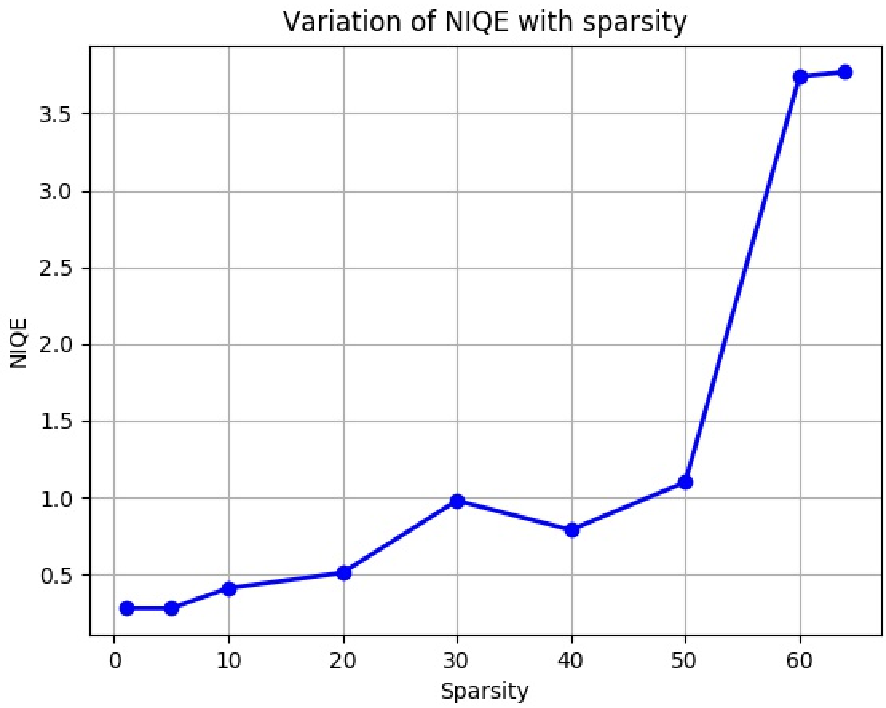


Figure 7: Plot depicting the variation of NIQE values with sparsity. The pattern suggests that NIQE values increase as the coefficient array is made less and less sparse.

References

[1] Anish Mittal, Rajiv Soundararajan, and Alan C Bovik. "Making a "completely blind" image quality analyzer". In: *IEEE Signal Processing Letters* 20.3 (2013), pp. 209–212.

[2] Bin Shen et al. "Image inpainting via sparse representation". In: *Acoustics, Speech and Signal Processing, 2009. ICASSP 2009. IEEE International Conference on*. IEEE. 2009, pp. 697–700.