CSIC 5011 Mini-Project 1: Image Inpainting with PCA

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1. Introduction

The image inpainting problem is common and important because it is a fundamental task in computer vision and image processing. It involves filling in missing or damaged parts of an image, which can occur for various reasons such as noise, occlusion, or physical damage. In traditional(not Deep Learning) solutions, one of the crucial steps is finding a suitable dictionary for the compact/sparse representation[1] of the image. Here, we use components learned from PCA to serve as the dictionary and do inpainting well in handwriting digits dataset.

2. Problem and Method

In this mini project, we applied three damage patterns to raw digits, illustrated in Fig.1. "Broken middle row/col" involves masking the middle rows or columns of the digit. "Broken cross" involves masking the middle rows and columns of the digit, resulting in a more severely damaged digit than the first two patterns.

In our approach, we followed these steps to perform image inpainting:

- Step 1: We applied Principal Component Analysis (PCA) on the training set of the dataset to determine the number of components k, based on the desired percentage of variance importance r and acquired the top-k important components as the base of the image dictionary.
- Step 2: Although we had a base dictionary, the representation of images in the dataset still had a complicated distribution in the base. We quantized the representation of training images in the base space using k-means clustering to get the dictionary can depict the distribution.
- Step 3: When performing inpainting, we first converted the damaged image into the base space and found its nearest center in the dictionary as its undamaged version representation. Finally, we converted the representation back to an image.

By using this approach, we could effectively fill in missing or damaged parts of images, restoring the semantic information of the image

Fig.1

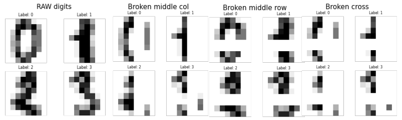


Fig.8

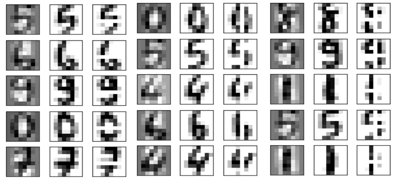
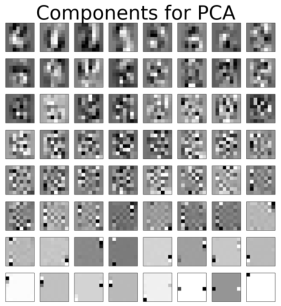


Fig.2



3. Dictionary Learned from PCA

The hand-written digits dataset consists of 1797 samples, of which we used the first 1597 samples as training images and the last 200 samples as testing images. We performed Principal Component Analysis (PCA) on the training images and obtained the results shown in Fig.2 and Fig.3.

Fig.2 visualizes all the components in PCA in decreasing order of importance, from left to right and top to bottom.

Fig.3 shows the importance of each component, and we determined that k=40 by selecting the top components that accounted for at least 99% of the variance importance. We also randomly choose four samples from training set and show the reconstruction result using the top-40 components in Fig.4. Notice that the reconstruction is

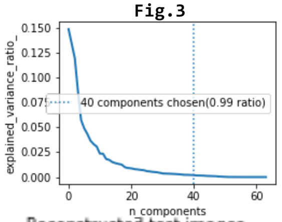
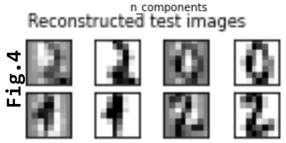
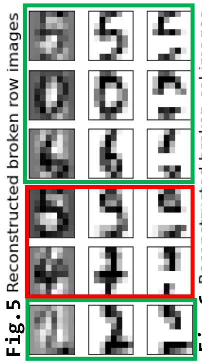
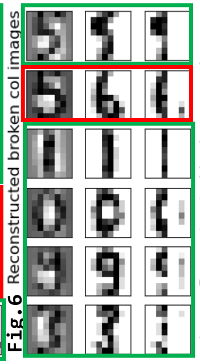
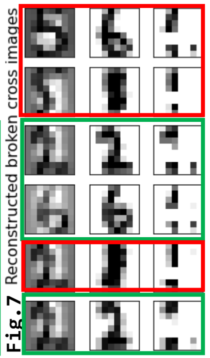


Fig.4









4. Inpainting Results Analysis

The results of inpainting row, column, and cross damage are shown in Figures 5, 6, and 7, respectively. Each figure includes three columns: the first column shows the reconstruction result, the second column shows the original image, and the third column shows the damaged image. The samples shown are randomly selected from test images.

Due to the concentration of effective pixels in the middle of hand-written digits, the information loss for inpainting increases from Figure 5 to Figure 7. Despite this, our method is able to reasonably inpaint the damaged areas and restore the semantic information in these scenarios (as shown by the green squares in Figures 5-7).

However, we have observed that the performance of our method is not stable, and occasionally fails to restore the correct semantic information. Nonetheless, the inpainting results are still reasonable digits.

It should be noted that in the previous damage pattern, we removed the middle two rows or columns, which resulted in a significant information loss of approximately 25% for row/column damage and 43.75% for cross damage, considering the small size of the 8x8 images. Therefore, our method is more likely to fail in these scenarios.

To further evaluate the effectiveness of our method, we also examined a moderate damage pattern where only one row or column is removed. The results are shown in Figure 8, which demonstrates that our method is able to successfully restore the correct information for all the randomly selected samples. This indicates that our approach is effective and stable in handling moderate damage.

5. Conclusion

In this mini project, we have presented a method for utilizing PCA to construct a dictionary for inpainting images on the hand-written digits dataset. Our approach has successfully restored semantic information for moderate damage scenarios, but it is not always stable when dealing with highly damaged images.

To further improve our method, future developments could consider handling more realistic and larger images. Additionally, constructing the dictionary from image patches rather than the entire image could also be explored. This would allow us to capture more local, fine-grained details and improve the accuracy of the inpainting results.

6. References

[1] Michael Elad and Michal Aharon. Image denoising via learned dictionaries and sparse representation. In Computer Vision and Pattern Recognition, 2006 IEEE Computer Society Conference on, volume 1, pages 895–900. IEEE, 2006
[2] https://yao-lab.github.io/course/csic5011/2023/slides/pca_logistic.ipynb