Sharif University of Technology
Electrical Engineering School

Advanced Neuroscience HW9
Based on Olshausen & Field 1996

EMERGENCE OF SIMPLE-CELL RECEPTIVE FIELD PROPERTIES BY LEARNING A SPARSE CODE FOR NATURAL IMAGES

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Part.1 - Sparse Basis Functions of the Natural Images

Using the 10 natural images of the paper, we want to calculate sparse basis functions for them. For that, we use the pre processed images of the paper which are whitend. Here's the 64 simulated basis functions each of them sized 8×8 of the Natural Images of the Paper:

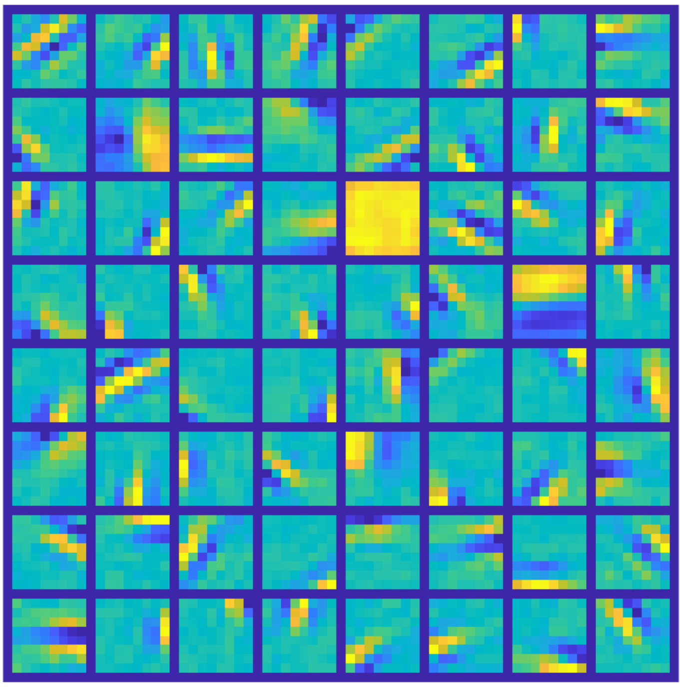

Figure 1: 64 8×8 Sparse Basis Functions of the Natural Images of the Paper

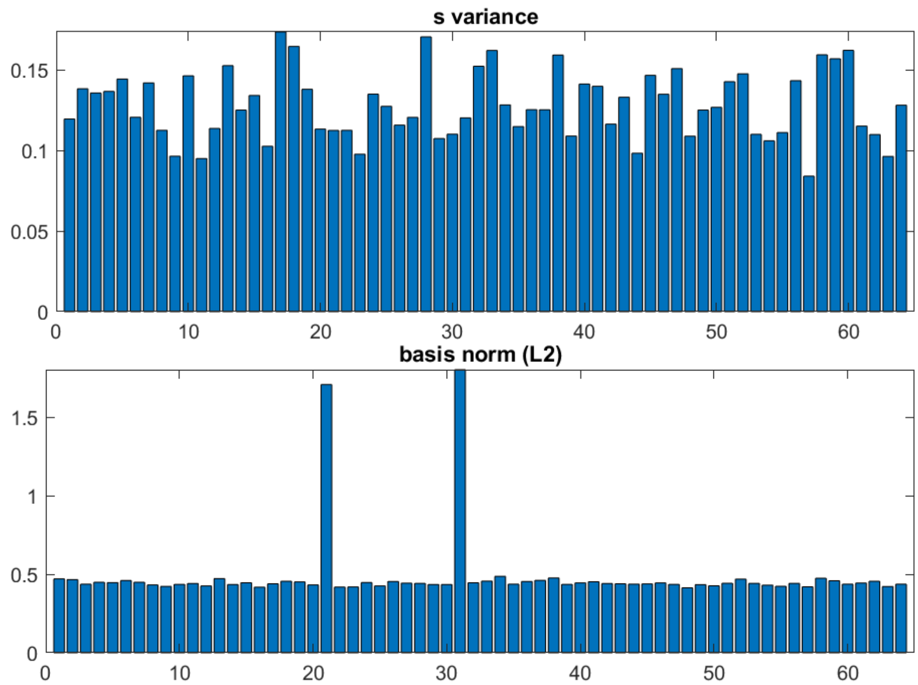

Figure 2: Sparse Coefficients Norm & Variance

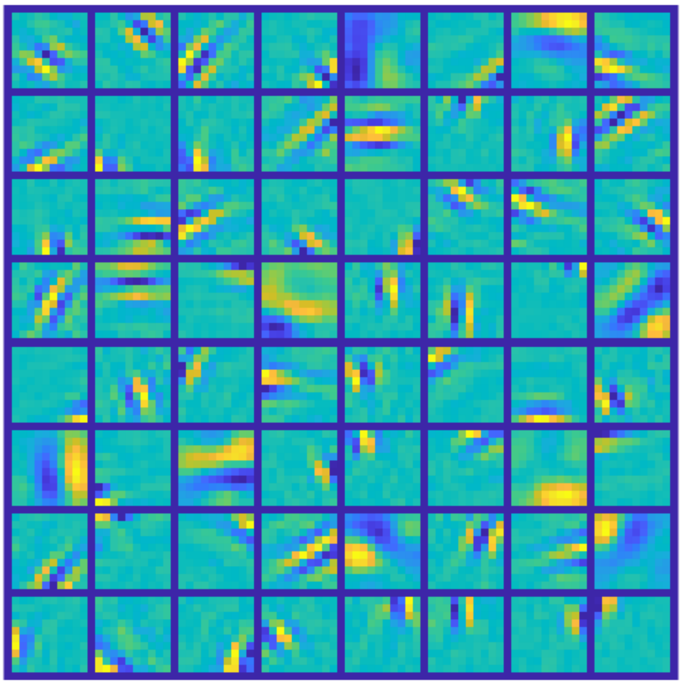

Figure 3: 64 10×10 Sparse Basis Functions of the Natural Images of the Paper

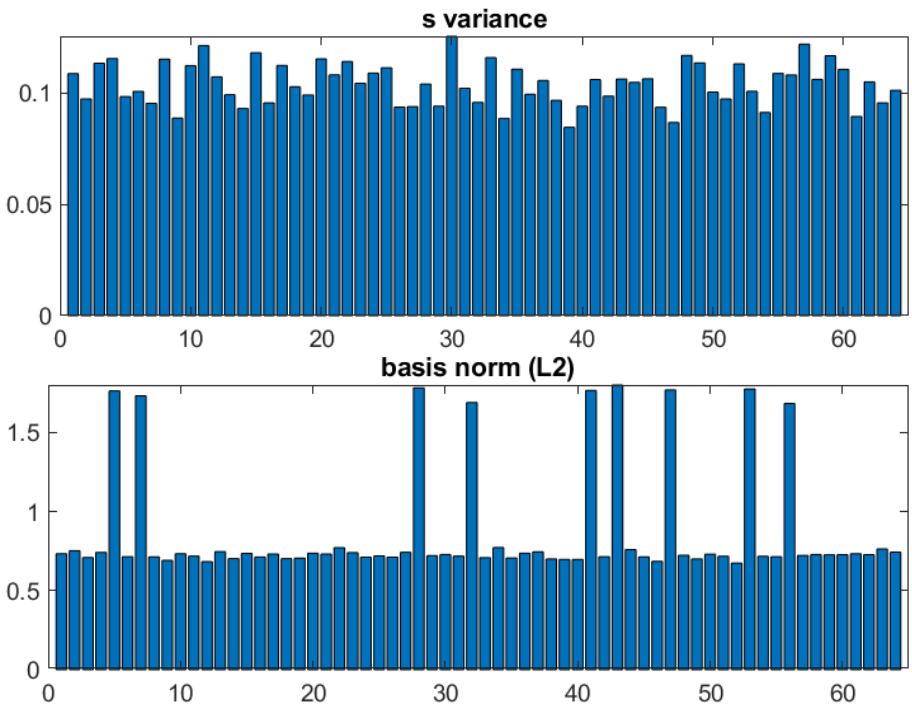

Figure 4: Sparse Coefficients Norm & Variance

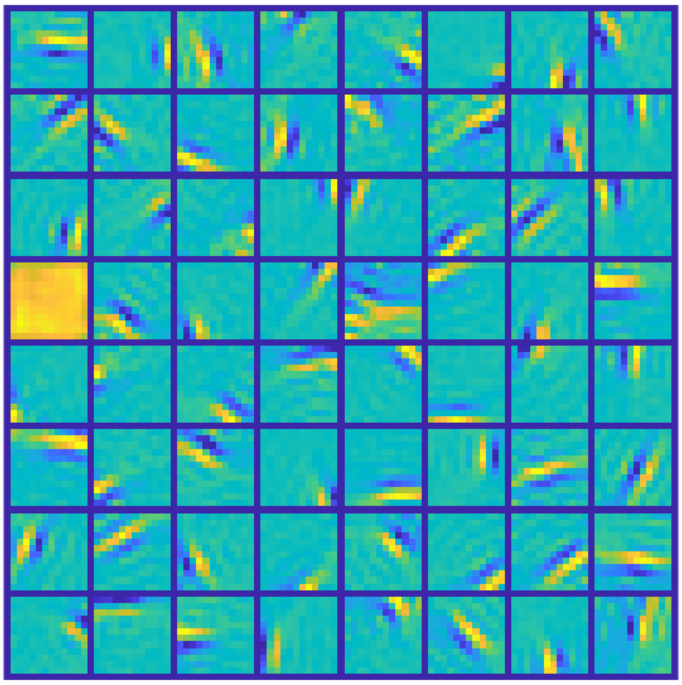

Figure 5: 64 12×12 Sparse Basis Functions of the Natural Images of the Paper

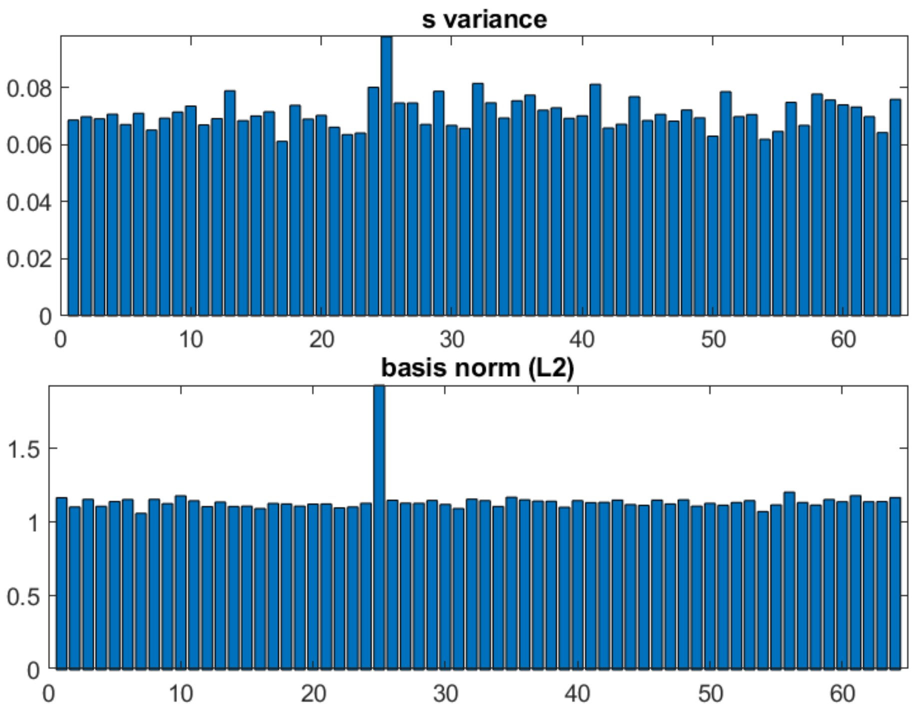

Figure 6: Sparse Coefficients Norm & Variance

As you can see, by increasing the size of basis functions, we have better basis functions with lower variances. In the end, as we expected, since the images are natural, simulated basis functions are shaped like simple cell receptive fields. They are localized and oriented and like Gabor function!

Part.2.1 - Sparse Basis Functions of the Yale Dataset Images

Using the Yale dataset, we have 2469 rectangle shape images. So at first, we crop images to be square shape. I've also shuffled the order of the images. In the end, for whitaning the images, I've normalized the images to the mean of 0 and variance of 1 and then give them to the "make your own images.m" to remove white noise from them. At the end of the function, variance of all images are set to 0.1 which is the goal variance of the sparsenet scrip. Here's the 64 8×8 basis functions simulated for 10 randomly chosen images from the dataset:

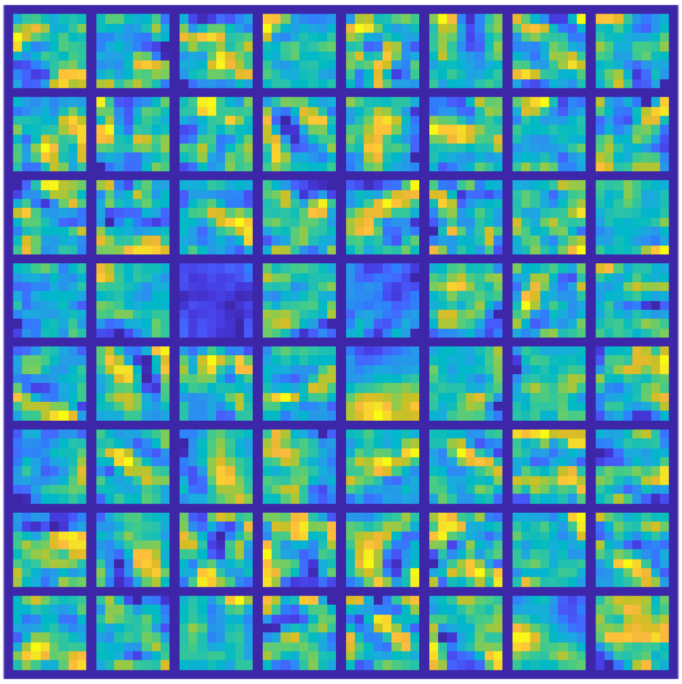

Figure 7: 64 8×8 Sparse Basis Functions of the Natural Images of the Paper

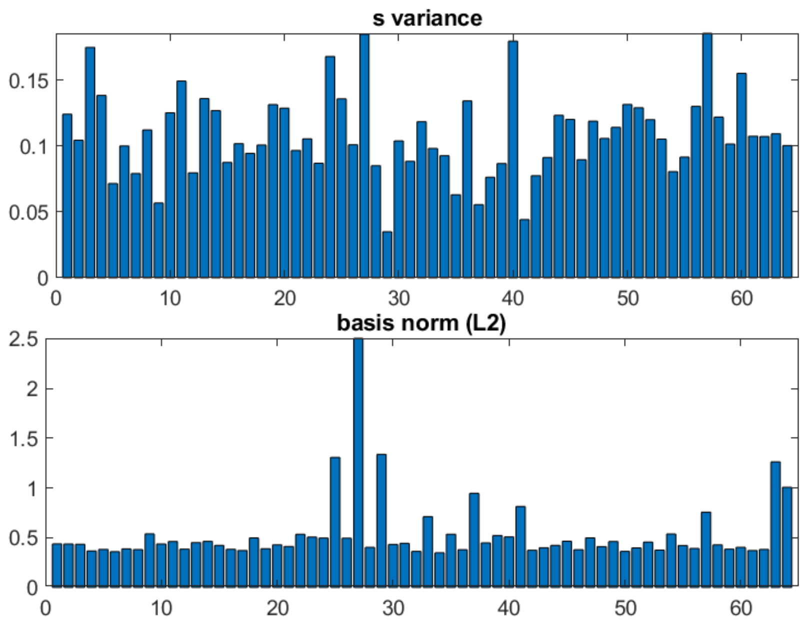

Figure 8: Sparse Coefficients Norm & Variance

As you can see, the simulated basis functions are not like the Gabor functions(like simple cell receptive fields). It's logical since the dataset we are using doesn't contain natural images:

Figure 9: 10 Random 168×168 Images Used for the Basis Functions Above

Maybe we get more sparse functions if we increase the size of them. Here's the results for 64 12×12 basis functions:

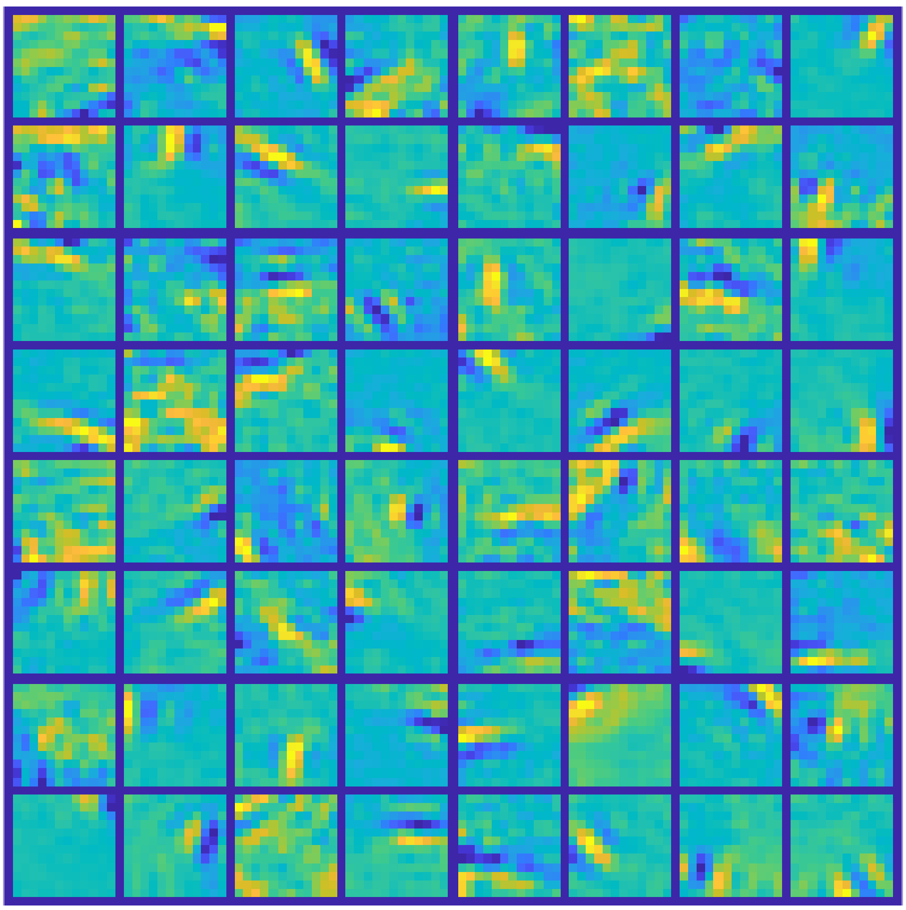

Figure 10: 64 12×12 Sparse Basis Functions of the Natural Images of the Paper

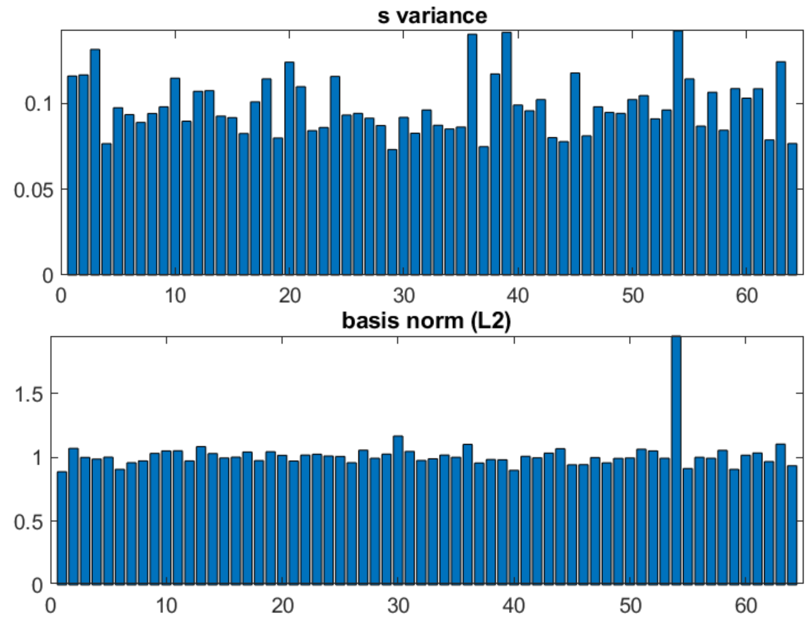

Figure 11: Sparse Coefficients Norm & Variance

As we expected, by increasing the size of basis matrix, we have better basis functions but they are not as good as basis functions of the natural images which we saw in the previous part.

Part.2.2 - Sparse Basis Functions of the MNIST Dataset Images

We do the pre processings like the previous dataset, and visualize the simulated basis functions. Below, you can find 64 6×6 basis functions for 10 random images of MNIST whitened images:

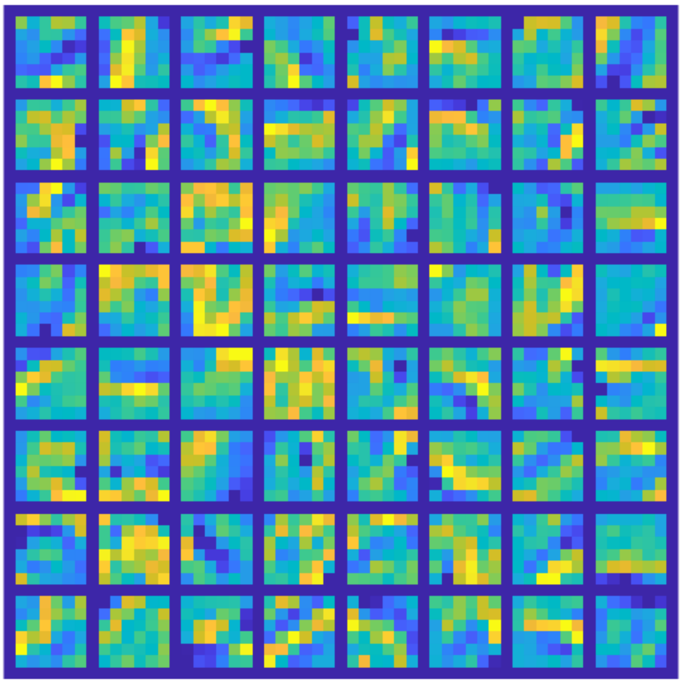

Figure 12: 64 6×6 Sparse Basis Functions of the Natural Images of the Paper

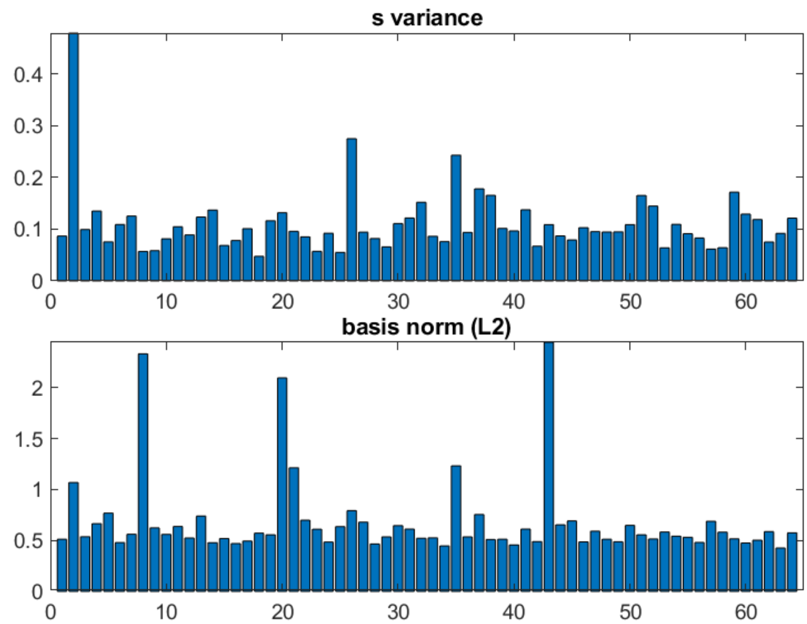

Figure 13: Sparse Coefficients Norm & Variance

As you can see above, the basis functions are not like simple cell receptive fields. They're not localized or oriented. Again since the MNIST dataset doesn't contain natural images, this is a logical observation. We can try increasing the size of basis function matrix and check if we see any changes:

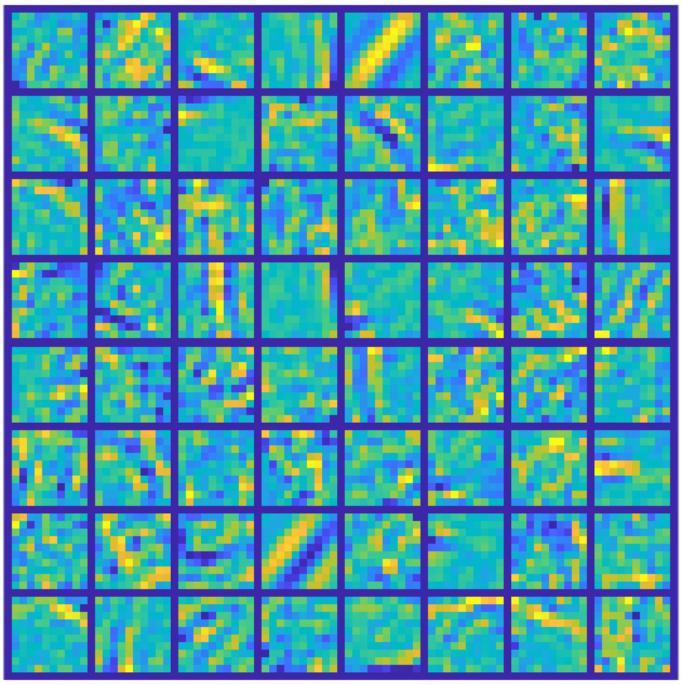

Figure 14: 64 10×10 Sparse Basis Functions of the Natural Images of the Paper

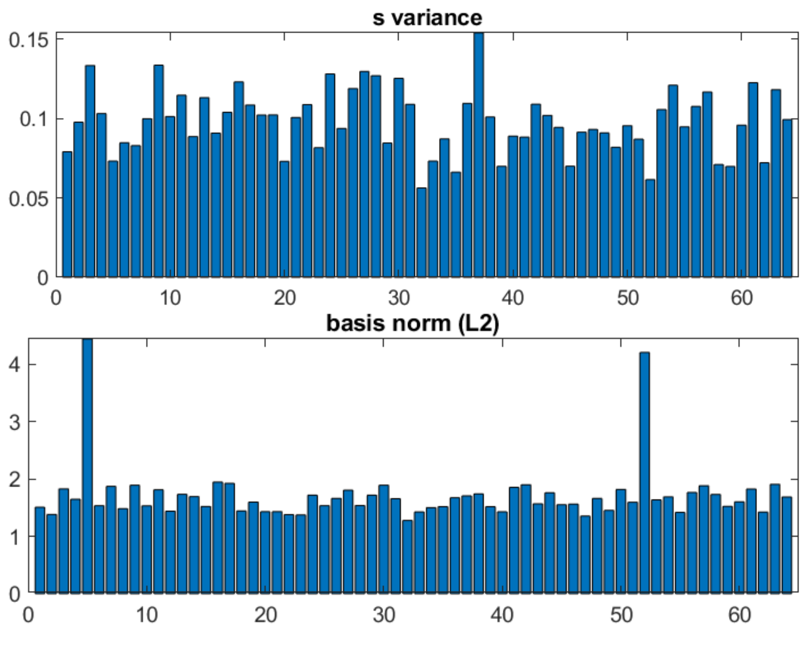

Figure 15: Sparse Coefficients Norm & Variance

It seems that some of the basis functions are now like receptive fields but in overall, the performance is weak. You can see some Gabor like, oriented basis functions but non is localized. Let's increase the size a bit more and check again:

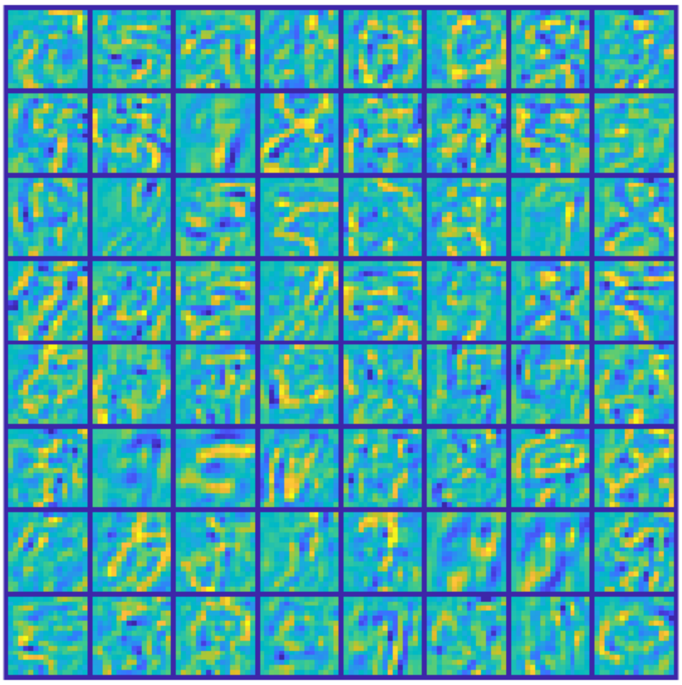

Figure 16: 64 16×16 Sparse Basis Functions of the Natural Images of the Paper

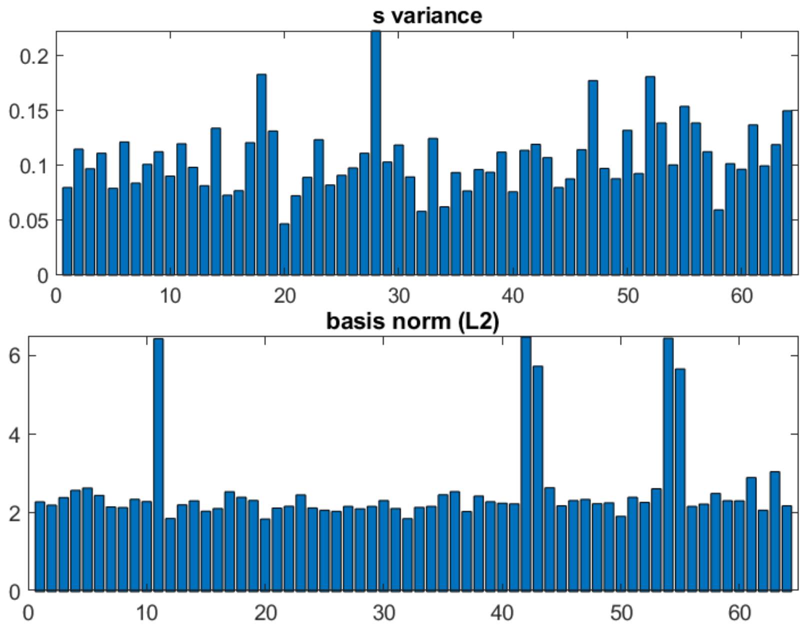

Figure 17: Sparse Coefficients Norm & Variance

As you can see, by setting the basis function matrix size very big, they will shape basis functions like our images which is obvious.

Part.2.3 - Sparse Basis Functions of the Caltech 101 Images

We do the pre processings like the previous dataset, and visualize the simulated basis functions. Below, you can find 64 6×6 basis functions for 10 random images of Caltech 101 whitened images:

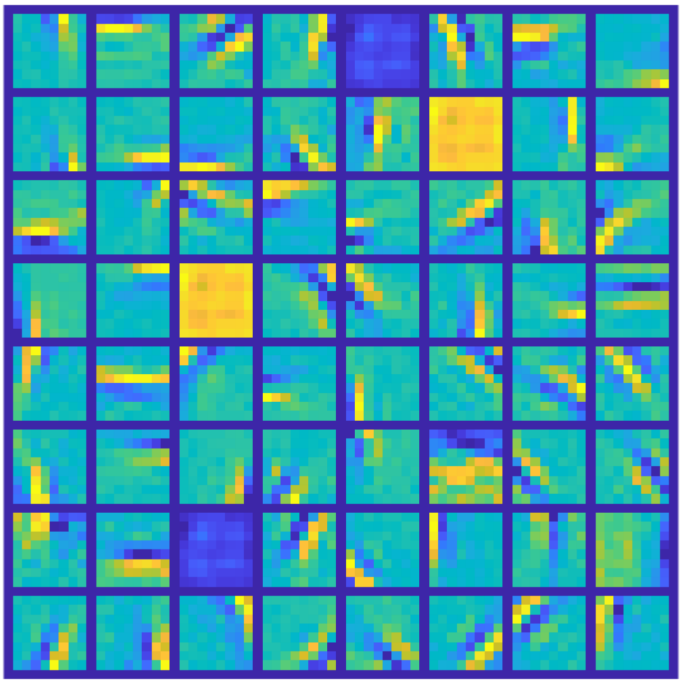

Figure 18: 64 8×8 Sparse Basis Functions of the Natural Images of the Paper

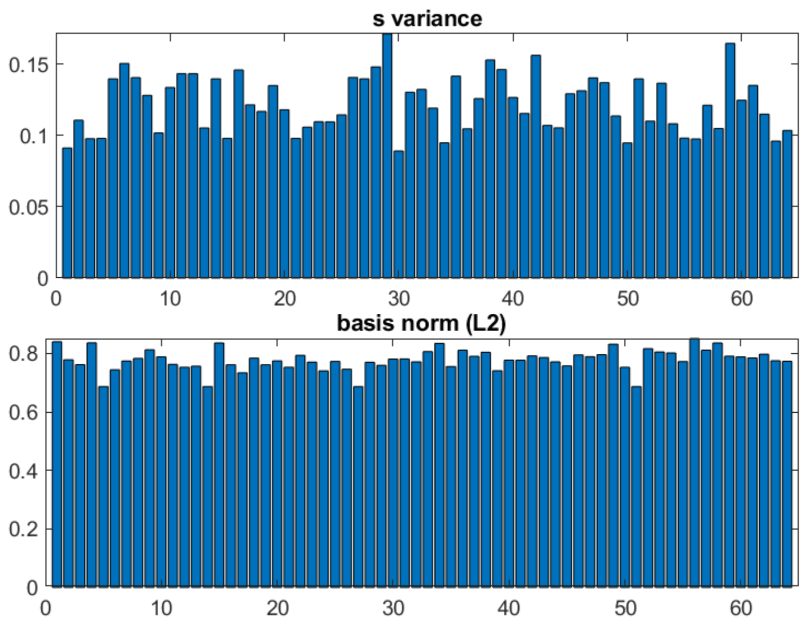

Figure 19: Sparse Coefficients Norm & Variance

Since this dataset contains natural images, we can see that our basis functions are Gabor like, localized and oriented. By increasing the size of the basis function matrix, we probably will have better basis functions:

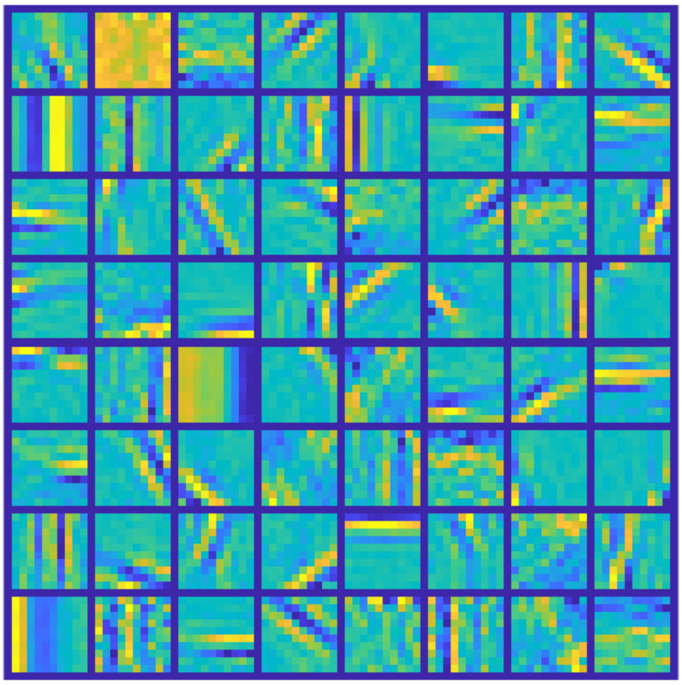

Figure 20: 64 10 × 10 Sparse Basis Functions of the Natural Images of the Paper

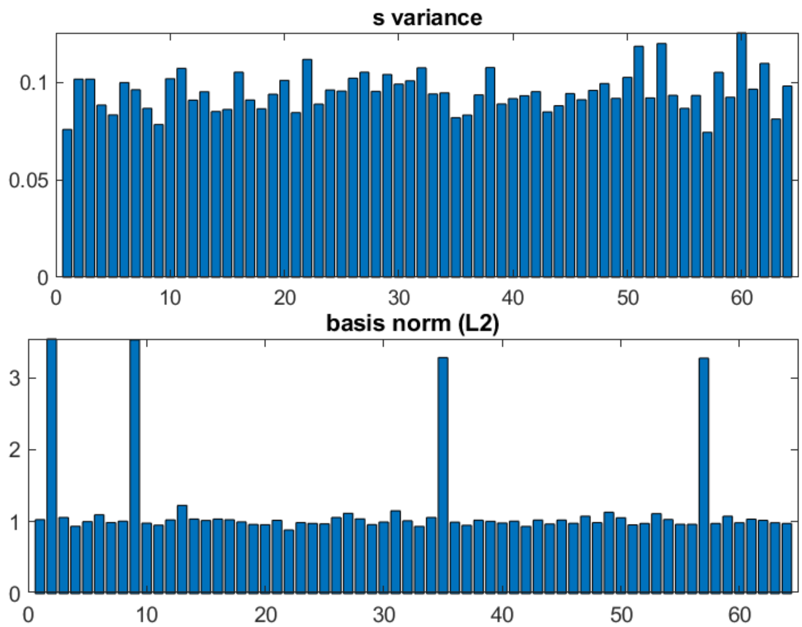

Figure 21: Sparse Coefficients Norm & Variance

Part.3 - Sparse Basis Functions & Coefficients of the Bird Video

I've calculated 64 basis functions of size 24×24 for the first 10 frames. Here's the result

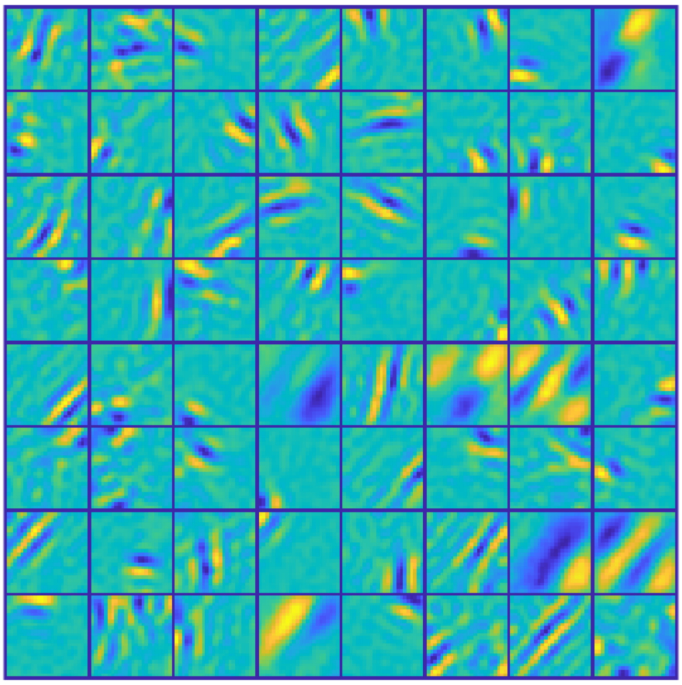

Figure 22: 64 24×24 Sparse Basis Functions of the Natural Images of the Paper

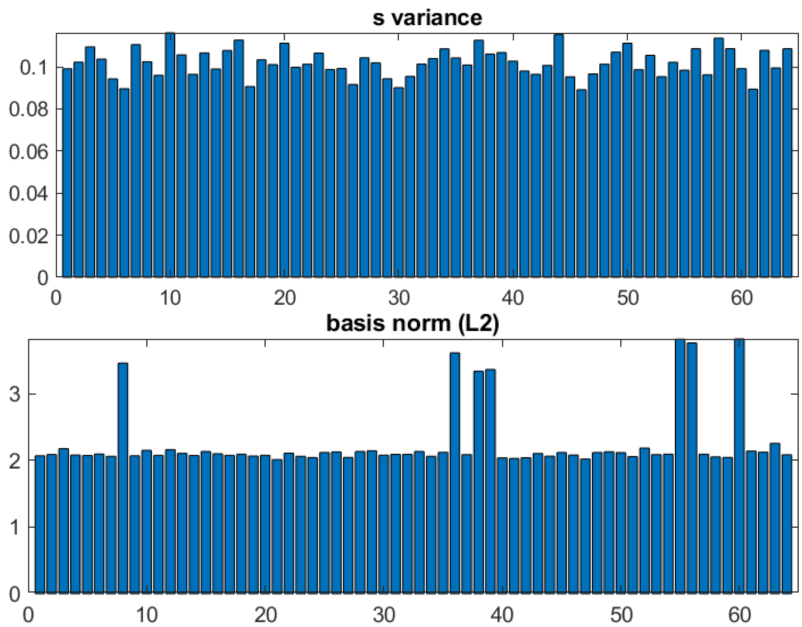

Figure 23: Sparse Coefficients Norm & Variance

Then I've calculated the sparse coefficients based for each frame divided in to patches of size of basis functions matrix and plot the sparse coefficients value vs frame(time) & window number and another plot which shows behavior of the coefficients of a single window (window 60) for all basis function through time:

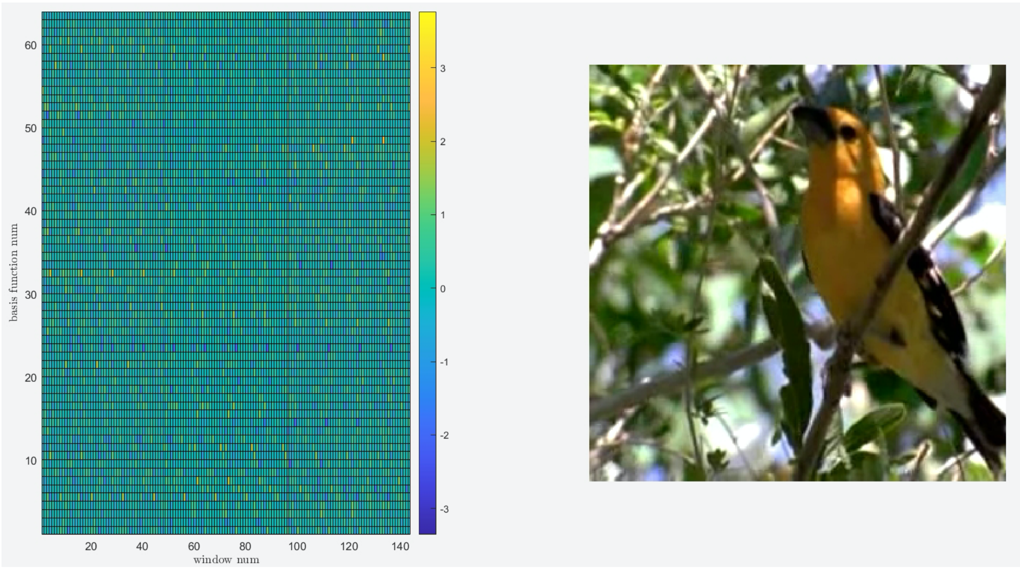

Figure 24: Snapshots of the Videos

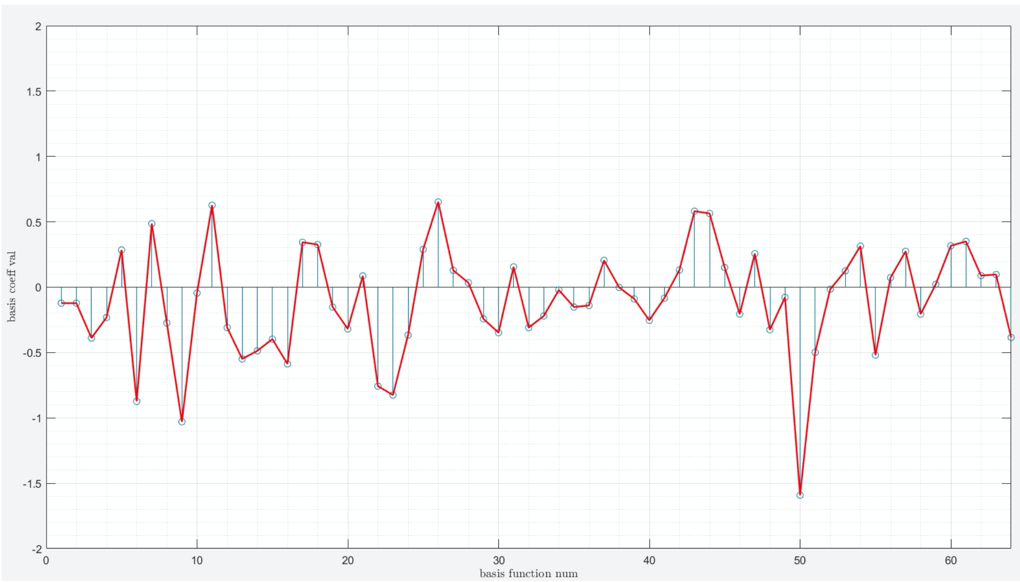

Figure 25: Snapshots of the Videos