Project Proposal: CS 754- Advanced Image Processing

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Paper chosen: [Compressed sensing using binary matrices of nearly optimal dimensions]

Objective: We aim to implement and evaluate the compressed sensing algorithms discussed in the above-mentioned paper written by Lotfi and Vidyasagar, focusing on their applicability to image processing tasks using l1-norm minimization (Basis Pursuit) for recovery. We shall compare the performance of binary measurement matrices (array codes, girth six related matrices, and DeVore matrices) with random Gaussian matrices in the context of recovering sparse representations of images.

Datasets: Like in the Homework assignments we are given, we will utilize standard grayscale image datasets commonly used in image processing research. Examples include:

- Small standard test images such as Lena, Barbara, Cameraman, House (typically of size 256x256 or 512x512). These images are widely used and allow for easy comparison with existing literature.
- Patches from larger image datasets => We might extract smaller patches (e.g., 32x32 or 64x64) from larger datasets like ImageNet to increase the diversity of image content.
- Kindly note that our dataset is custom to change. When we asked an LLM for dataset recommendations, it suggested using Synthetic Sparse Vector Datasets (for baseline comparison and validation), something which we are not entirely considering at the moment because we are more interested in the applicability of the algorithms in the context of Image processing.

Sparse Representations: As taught in class, for these image datasets, we will utilize the concept of sparse representations in a transform domain like the DCT. We will obtain a sparse representation of the images by applying the chosen transform and then keep only the largest k coefficients (in magnitude), and thereby setting the rest to zero.

Measurement Matrices: We will use the measurement matrices which have been mentioned in the paper, which are namely: Array Code Binary Matrices, Euler Square Based Binary Matrices, DeVore Binary Matrices, Random Gaussian Matrices.

Evaluation/Validation Strategy: Our evaluation strategy will now include assessing the performance of compressed sensing with binary matrices for image recovery using Basis Pursuit. The steps are briefly mentioned as follows:

- Obtain a sparse representation of the chosen images by keeping the top k coefficients and set the smaller values to zero, thereby giving us a k-sparse vector named x.
- Generate measurements by multiplying the sparse coefficient vector (x) with the measurement matrix (A): y = Ax.
- Attempt to recover the sparse vector ($\hat{x}$) from the measurements (y) using Basis Pursuit: argmin $||z||_1$ such that $||y - Az||_2 \leq \varepsilon$ (where ε might be small to account for noise, or 0 for ideal noiseless scenarios). We will use a standard optimization package in MATLAB for this.
- After recovering $\hat{x}$, we will apply the inverse transform to obtain the reconstructed image and gauge the performance using suitable performance metrics as mentioned below.
- Performance Metrics: Peak Signal-to-Noise Ratio (PSNR), Root Mean Square Error (RMSE). Another metric as suggested by an LLM is Structural Similarity Index Measure **(SSIM),** which is a perceptual metric that assesses the similarity between two images by considering luminance, contrast, and structure. SSIM values range from -1 to 1, with 1 indicating perfect similarity.
- We will vary the sparsity level k (number of kept transform coefficients) and the number of measurements m to observe their effect on the recovery performance for different types of binary and Gaussian measurement matrices.
- We will compare the PSNR, RMSE and SSIM (wherever applicable) values obtained with binary matrices (array codes, Euler square based, DeVore) against those obtained using random Gaussian matrices for different under sampling ratios and sparsity levels. This will help us assess the viability of binary matrices as alternatives to Gaussian matrices in practical image processing scenarios using Basis Pursuit.

Computational Efficiency (if time permits): We will also measure and compare the CPU time for generating the measurement matrices and for performing Basis Pursuit for image recovery with each type of matrix.

By incorporating image datasets and relevant evaluation metrics, we will be able to assess the practical utility of the compressed sensing algorithms with binary matrices, specifically in the context of image processing and using Basis Pursuit as the recovery method.