TITLE SLIDE

Hello, we are Gloria Diederich, Alyson Grassi, and Molly Nichols.

We have chosen to discuss image deblurring and its relationship to matrix theory and to practical applications. In particular, we will focus on a topic of practical interest in real-world applications – blind image deconvolution.

OUTLINE SLIDE

We’ll first walk through a quick introduction to the problem and why it is significant, along with introducing some terminology. We’ll then move into more details about the model of the problem. Finally, we’ll show some results using Matlab and our conclusions.

WHAT IS IMAGE DEBLURRING SLIDE

First we ask – what is image deblurring? Bascially, it is essentially what it sounds like. Given some degraded or blurred image, we would like to recover as much information as possible about the original image and restore that quality to it.

Images have become so ubiquitous, for personal, public, and scientific purposes. Think about how useful images are for things like security footage, medical screening, remote sensing, astronomical exploration…the list goes on. Of course, we’d like the best possible quality images for these applications, but there are numerous issues that could occur, such as motion blur, incorrect system calibration, unexpected environmental effects, transmission errors, and many more. Ultimately clarity in images can define the results in certain fields of research. Image deblurring can help us achieve the necessary image quality for serious applications like these.

As we’ve seen already, matrices can represent images and therefore the theory behind matrices is interwoven in this application.

WHAT IS BLIND DECONVOLUTION SLIDE

If we think of the blurred image as a convolution of two sources (the image of desired quality and the blur), we can begin to develop a mathematical process of acquiring the ideal image. This is more straightforward when we know the degradation of the image – we could use the convolution and the degradation to find the ideal image, basically reversing the blur’s affects. A more prevalent problem in real world applications is when the degradation of the images is not known, when perhaps multiple effects are at play, and perhaps in different magnitudes. This is a harder, but very relevant, problem: the convolution of the two sources is known, but neither the blur nor the ideal image is known. This makes acquiring the ideal image more difficult. The separating the blur and the image, is called the “deconvolution” of the blurred image, and achieving this without knowledge of either sources of the convolution – is known as blind deconvolution. The solution to this problem generally involves some sort of iterative process or algorithm to find the maximum likelihood of the two sources.

MODEL TERMINOLOGY

In order to construct our model, we define g as the convoluted signal of the ideal image and blur, f as the image source or ideal image, h as the Point Spread Function or blur and n as additional noise. The basis of our model is shown in the first equation. The bottom graphic shows how g is created. Our goal is to go backwards to find both h and f ultimately. These functions have 3 dimensions, x, y, for pixel location and a z for the image data in that pixel.

MODEL ALGORITHMS

The collected image data has a likelihood of being produced by a particular source because of the random nature of quantum photon emissions. The Maximum likelihood estimation is a method of creating best estimates of data effected by random noise by finding the estimate of f from convolution equation that is most likely to have given rise to the data collected.

This is achieved by creating a ``logarithmic-likelihood function'' representative of the likelihood that a certain level of noise is measured in the collection of data. This functional, a function of f(), h() and g(), is solved iteratively to calculate its maximum value. A reconstructed image, f(), and reconstructed PSF, h(), are found using an iterative search. A more detailed look on this algorithm is given in Holmes.

This algorithm operates under the assumption that the original image was degraded due to any of the aforementioned causes and these can be represented with a PSF. Iterative algorithms, such as the R-L algorithm, tend to be more accurate when restoring degraded images because they take into account the potential presence of noise, which often occurs in practical applications. The R-L algorithm employs the expectation-maximization algorithm in order to determine a restored image that most accurately represents the original image. Thus, this algorithm assumes that the degraded image was formed through a Poisson process meaning the degraded image has signal-dependent noise corruption