PRACTICAL CONSIDERATIONS IN EXPERIMENTAL COMPUTATIONAL SENSING

by

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As members of the Dissertation Committee, we certify that we have read the dissertation prepared by Phillip K. Poon titled Practical Considerations in Experimental Computational Sensing and recommend that it be accepted as fulfilling the dissertation requirement for the degree of Doctor of Philosophy.

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I hereby certify that I have read this dissertation prepared under my direction and recommend that it be accepted as fulfilling the dissertation requirement.

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DEDICATION

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

Implementing computational optical sensors often comes with various issues that many traditional sensors may not encounter.

CHAPTER 1

Introduction

This chapter introduces the reader to the concept of computational sensing and provides the motivation for the need to address the practical issues in experimental computational sensing.

Computational sensing is the concept that a joint design of the sensor hardware, often though coding of the analog signal combined with task-specific algorithms can exceed the performance of a traditional sensor, which we call *isomorphic sensors*. While isomorphic sensors can provide flexible sensing in multiple applications. A computational sensor's joint design, which considers both the architecture of the sensor, coding of the analog signal and often geared towards a specific task naturally lends to performance increases [1]. Throughout this chapter and the rest of this dissertation we will provide many examples that highlight the differences between computational and isomorphic sensing.

Rather than a rigorous discussion, this chapter will discuss some of the major developments and contributions to the field of computational sensing on an intuitive level. This will familiarize the reader with important terminology and techniques common in the computational sensing community. The projects presented in this dissertation are a natural evolution of these developments. A rigorous discussion of the concepts is given in chapter 2. Then I will briefly discuss some of the challenges I and many other experimentalists and engineers have faced when developing computational sensing prototypes. Then the chapter will close with a brief look ahead to the rest of the dissertation.

1.1 Major Developments in Computational Sensing

1.1.1 Isomorphic Sensing

In Greek, the word isomorphic loosely translates to equal in form. Traditional sensors perform isomorphic sensing. In the context of this dissertation, an isomorphic sensor is any sensor which attempts to produce an output signal that resembles the signal-of-interest. In this paradigm, the analog instrument, sampling scheme, and post-processing algorithms are seperated, see Figure 1.1.

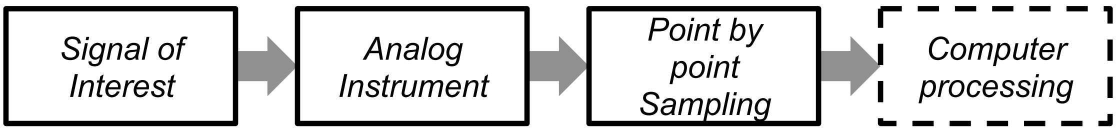

Figure 1.1: A systems view of a traditional sensing scheme. The signal-of-interest is incident upon the analog instrument. The analog instrument forms an isomorphism of the signal which is then periodically sampled point-by-point through an ADC device. Once the signal is in digital form, post-processing algorithms are often used to perform various tasks such as noise reduction, detection, and classification. Notice that the analog instrument, sampling scheme, and processing are all seperated.

We will discuss two important examples of isomorphic sensors: the photographic camera and the optical spectrometer (which I will just call a spectrometer from now on, even though there are many instruments called spectromers that not concerned with optical spectra). These two sensors have had major roles in throughout the history of optics and in the physical sciences and so it is natural that they have also been the main focus of computational sensing. Therefore it is important we first understand the isomorphic version of these sensors.

In the camera, the signal-of-interest is the object that is being photographed. This can be anything that is scattering or emitting light, a person, a tree or a distant group of stars. The analog instrument consists of the lens which is designed and fabricated to produce an image that is looks like the object at the focal-plane array (FPA). The more that the image resembles the object the better the optics. The FPA then samples and quantizes the image and produces a digital representation of the object, measurement data. The measurement data is often is post-processed using algorithms to increased desired effects such noise removal or to locate the object.

There are two major components in the camera which determine how well it performs: the optics and the FPA. Ideally, the optics (the analog instrument in this case) will produce a point spread function (PSF) which is infinitely small in diameter. For example, in a task such as the detection of a star from several neighboring stars in the night sky, if the PSF is much larger than the center to center seperation of the two stars in the optical image, it will be quite difficult to detect. A careful reader will note that this is the same argument used by Lord Raleigh in proposing his resolution criterion [2]. Even if the PSF is small enough, the FPA must sample at a fine enough pixel-to-pixel spacing, called the *pixel pitch*, to accurately reproduce the intensity variations at the scale which is pertinant to the task. Intuitively, this makes sense because if the image of both stars and the decreased intensity which signifies a certain amount of seperation between the two stars is imaged onto a single pixel, the one cannot ever hope to be able to accurately the detect the star without some other prior or side information. Shannon, Nyquist, Wittaker and others established the theory for determining what the pixel spacing must be in order to properly sample the analog signal without loosing any information [3, 4, 5].

In the spectrometer, the signal of interest is the spectrum of the object. The optics are designed to take the incoming light and seperate various wavelength components. The part of the spectrometer which is used to physically isolate the wavelengths is called a *spectrograph*. The result is a spectral intensity as a function of position at the FPA. The FPA and post-processing algorithms are used in the same manner as the photographic camera, which is to sample the optical spectrum creating digital version of it and to perform various tasks on the measurement data. To simplify our discussion, we will concentrate on the slit spectrometer, which spectrum at a single point on the object.

In the spectrometer, one of the important performance metrics is *spectral resolution* which we denote $\delta\lambda$. The spectral resolution is the smallest difference in wavelength the instrument can discern. As in the camera, the optical components plays a major role in determining the spectral resolution. Large spectral resolutions can degrade the spectrometers ability to discern important parts of the spectrum we are testing. Similarly with the camera, the FPA must have a pixel pitch which is small enough in order to correctly sample the variations in the spectrum.

At each instant in time, or exposure, the readout from the FPA produces a single number per pixel. Pixel's number represents a single sample of the signal-of-interest. This is both the strength and weakness of the isomorphic sensor. The strength comes the straightforward and intuitive architecture of the isomorphic sensor. Each subsystem; the optics, the FPA, and the post-processing can be designed and constructed seperately so long as they meet their individual specifications. As long as the signal to noise ratio is sufficient, something we can change by adjust exposure time, and we sample at a rate high enough we are garuenteed to recovery the signal.

he weakness comes from The point-by-point nature of the sampling scheme which is part of the in isomorphic sensors parallel nature of the FPA in sampling the intensity distribution of the signal is that of the traditional camera architecture that we just mentioned is t

1.2 Dissertation Overview

CHAPTER 2

Formalism

This chapter introduces the reader to the more rigorous concepts and mathematical background that will required to fully understand the material presented in the later chapters of this dissertation.

A rigorous discussion of multiplexing and signal-to-noise ratio will be discussed, as well are various coding schemes used in various notable computational sensors as well as the ones in this disseration.

Since the AFSSI-C relies on a variation of Principal Component Analysis (PCA) and a Bayesian algorithm for coding design we will discuss some of the fundamental of Bayesian probability and the Log-Likelihood Ratios.

2.1 Multiplexing

2.2 Principal Component Analysis

2.3 Bayesian Rules and Log-Likelihood Ratios

2.4 Compressive Sensing

2.4.1 The Nyquist-Shannon Sampling Theorem

The Nyquist-Shannon Sampling Theorem states one must sample a signal with a sampling rate that is at least twice the maximum frequency of the signal to prevent aliasing [3].

2.4.2 Sparsity, Incoherence, and the Restricted Isometry Property

2.4.3 Inversion

2.4.3.1 L0 and L1 Norm Minimization

2.4.3.2 LASSO and sparsity regularization

Acronyms

AFSSI-C Adaptive Feature Specific Spectral Imaging-Classifier. 4, 5, 14

DISP Duke Imaging and Spectroscopy Program. 5

FPA focal-plane array. 12, 13

LCOS Liquid Crystal on Silicon. 5

LENS Laboratory for Engineering Non-Traditional Sensors. 4, 5

PSF point spread function. 12

SCOUT Static Computational Optical Undersampled Tracker. 5

SLM Spatial Light Modulator. 5

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