MANIFOLD LEARNING FOR MULTI-SENSOR, MULTI-RESOLUTION FUSION WITH IMPRECISE DATA

By

CONNOR H. MCCURLEY

A ORAL QUALIFYING EXAM PROPOSAL PRESENTED TO THE GRADUATE SCHOOL
OF THE UNIVERSITY OF FLORIDA IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

UNIVERSITY OF FLORIDA

2019

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1
INTRODUCTION

During this project, techniques will be explored for use in multi-sensor target detection, target classification, and information fusion given uncertain and imprecise groundtruth. These methods will be developed as universal approaches for fusion and will be evaluated on a variety of sensor modalities, including: mid-wave IR, visible, hyper-spectral and multi-spectral imagery, as well as LiDaR, ground-penetrating radar and electromagnetic induction sensors. The aim of this project is to develop fusion methods which can address mis-registration between sensor sources as well as uncertainty and imprecision in training data groundtruth while demonstrating robustness towards outlying and adversarial data points.

Multi-sensor fusion methods aim to amalgamate data collected from multiple information sources to reduce uncertainty and provide a greater level of understanding than can be obtained from the modalities, individually **CITE Xiaoxiao Paper**. Fusion of multiple sensor sources providing complimentary or reinforcing information is often paramount to the success of remote sensing applications. **provide intuitive example**

describe homogeneous/ heterogeneous fusion methods

Information fusion approaches make two assumptions, (1) the data to be fused are homogeneous (of the same data type and with the same resolution) and (2) training labels are available for each data point **CITE**. If fusing multiple heterogeneous sources (varying types and resolutions), it is assumed that individual data points can be matched together **CITE**. In other words, standard methods require data from m different sensors to produce data with one-to-one correspondence, or that some form of pre-processing can transform all sources to the same resolution and perform matching **CITE**.

is extracted through sensor-specific pipelines before fusion on the sample, feature, or decision level. There is an assumption under this approach that each pipeline extracts information with an adequate level of precision. However, overall performance is sensitive to each sensors' processing and information is often lost through co-registration. As an example, consider a self-driving car outfitted with an RGB camera and LiDAR (light detection and ranging) system. The goal of this computer vision system is to understand the scene around the vehicle so it may navigate safely. Classical approaches would perform pre-processing, feature extraction, and segmentation/ depth-map estimation on each sensor, individually. Co-registration would then be performed by mapping a single measurement from the dense LiDAR point-cloud to every pixel. However, if the wrong LiDAR point is assigned to a pixel, even just a small shift, the car's depth perception can be thrown off. This is information loss we cannot afford. A more intuitive method for fusion would be to first project each sensors' collection into a combined representation space before running on a unified pipeline such that the entirety of each sensor's collection is utilized.

Additionally, even assuming that homogeneously registered data is available for fusion or that there is a noiseless way to transform heterogeneous data, standard supervised learning methods require accurate labels for each training data point**CITE Xiaoxiao Dissertaion**. However, data-point specific labels are often unavailable or difficult and expensive to obtain **CITE Xiaoxiao dissertation reference 10**. **describe need for MIL**

Propose work

Briefly describe experiments and evaluation techniques

CHAPTER 2
BACKGROUND

CHAPTER 3
PROBLEM DESCRIPTION

CHAPTER 4
TECHNICAL APPROACH

CHAPTER 5
EXPERIMENTAL DESIGN

CHAPTER 6
PRELIMINARY WORK

CHAPTER 7
FUTURE TASKS

CHAPTER 8
CONCLUSIONS

REFERENCES