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

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INTRODUCTION

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**. Fusion of multiple sensor sources providing complimentary or reinforcing information is often paramount to the success of remote sensing applications. **Provide intuitive example:** Take the task of automatic target recognition (ATR) as an example, where the goal is to locate both armored vehicles and people subject varying environmental conditions. Imagery can be obtained from multiple sensors such as mid-wave infrared (MWIR), visible-spectrum, and hyperspectral cameras. Hyperspectral can provide a broad range of spectral information about the materials present in a scene, while MWIR imaging sensors can supply thermal information.

Information fusion approaches make two typical assumptions. (1) If fusing multiple heterogeneous sources (varying types and resolutions), it is assumed that individual data points can be co-registered (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**. (2) Training labels are available for each data point **CITE**.

–(**Loss of information, noisy transformations**)

Two problems arise from these assumptions. First, when working with sensors operating at varying spatial and temporal resolutions it is not necessarily feasible to convert all data to the same resolution or to map to the same grid **CITE** and existing co-registration approaches often result in loss of sensor-specific information **CITE**. **Provide intuitive example**

–(**Physical limitations, cost of labeling**)

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**. However, data-point specific labels are often unavailable or difficult and expensive to obtain **CITE**. **Provide intuitive example**

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. Roughly, the following research questions will be addressed during the scope of this project:

1. Can manifold learning be extended to operate under the multiple-instance framework? If so, what is the "best" way to construct the data manifold? Can manifold learning provide robustness to outlying and adversarial exemplars?

2. Can we construct a joint-representation space for multiple sensors such that there is no loss of information amongst any of the modalities? What is the "best" way to construct this representation? Do we use raw data or perform feature extraction before combination?

3. Can we perform detection/ segmentation using a single, sensor-agnostic processing pipeline on the unified representation? How do we obtain representative quantitative evaluation of performance?

Experiments will be conducted on both synthetic data and real applications such as plant phenotyping, as well as target detection and scene understanding in remote sensing imagery. Initial results demonstrate the aptitude of the proposed approaches and suggest further development and evaluation of these methods.

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