International Journal of Monitoring and Surveillance Technologies Research
Volume 5 • Issue 3 • July-September 2017

Manifold Transfer Subspace Learning (MTSL) for Applications in Aided Target Recognition

Olga Mendoza-Schrock, Air Force Research Laboratory, Wright-Patterson Air Force Base, USA
Mateen M. Rizki, Wright State University, Dayton, USA
Vincent J. Velten, Air Force Research Laboratory, Wright-Patterson Air Force Base, USA

ABSTRACT

This article describes how transfer subspace learning has recently gained popularity for its ability to perform cross-dataset and cross-domain object recognition. The ability to leverage existing data without the need for additional data collections is attractive for monitoring and surveillance technology, specifically for aided target recognition applications. Transfer subspace learning enables the incorporation of sparse and dynamically collected data into existing systems that utilize large databases. Manifold learning has also gained popularity for its success at dimensionality reduction. In this contribution, Manifold learning and transfer subspace learning are combined to create a new system capable of achieving high target recognition rates. The manifold learning technique used in this contribution is diffusion maps, a nonlinear dimensionality reduction technique based on a heat diffusion analogy. The transfer subspace learning technique used is Transfer Fisher's Linear Discriminative Analysis. The new system, manifold transfer subspace learning, sequentially integrates manifold learning and transfer subspace learning. In this article, the ability of the new techniques to achieve high target recognition rates for cross-dataset and cross-domain applications is illustrated using a variety of diverse datasets.

KEYWORDS

Diffusion Maps, Manifold Learning, Target Recognition, Transfer Learning, Transfer Subspace Learning

DOI: 10.4018/IJMSTR.2017070102

INTRODUCTION

Transfer Subspace Learning (TSL) has found a diverse range of applications, including cross-domain face recognition and text categorization (Si, Tao & Geng, 2010; Yang, Lin, Hou, Zhang & Wu, 2012). TSL is an enabler for data fusion and dynamic model building, an important component for Dynamic Data Driven Application Systems (DDDAS) (Blasch, Seetharaman & Darema, 2013). The focus of this study is to extend the TSL framework by combining it with Manifold Learning for a robust Aided Target Recognition (AiTR) system capable of achieving high target recognition rates for cross-dataset and cross-domain target recognition.

We seek to build an AiTR system that is robust to different operating conditions (Kahler, Blasch & Goodwon, 2007) including sensor modality, lighting conditions, shadows, weather, sensor type, terrain, image quality, and quality of metadata (Bryant, Johnson, Brian, Nowak & Rogers, 2008). A robust AiTR system would leverage all available 'similar' data to recognize a new target of interest to avoid having to collect large amounts of data on a new target before a recognition model could be built.

Data collections are resource intensive and costly, on the order of tens of thousands to a million dollars depending on the scope of the collection, the number of sensors utilized, and the complexity of the scenarios. Often, AiTR systems which are built utilizing data from a particular data collection suffer from dramatic performance loss when utilizing data from a different data collection or under real-world scenarios. By utilizing TSL, AiTR systems can be extended to dynamic systems where they are more robust and applicable to scenarios outside of the ones from which they were developed.

In this contribution, Manifold Learning and Transfer Subspace Learning are combined to create new dynamic Aided Target Recognition (AiTR) systems capable of achieving high target recognition rates for cross-dataset conditions and cross-domain applications. The Manifold Learning technique used in this dissertation is Diffusion Maps, a nonlinear dimensionality reduction technique based on a heat diffusion analogy. The Transfer Subspace Learning technique used is Transfer Fisher's Linear Discriminative Analysis, based on the standard Fisher's Linear Discriminative Analysis. The new AiTR system introduced is Manifold Transfer Subspace Learning, which combines Manifold Learning and Transfer Subspace Learning *sequentially*.

Finally, the ability of the new techniques to achieve high target recognition rates for cross-dataset and cross-domain applications is illustrated using a diverse set of datasets. The datasets include (1) the electro-optical (EO) synthetic vehicle dataset, (2) the MNIST handwritten digits dataset. The cross-dataset experiments use information about a set of objects under one set of operating conditions to recognize the same set of objects under a different set of operating conditions. For instance, using the electro-optical (EO) synthetic vehicle dataset, we use information about a set of vehicles under one set of lighting conditions to recognize the same set of vehicles under a different set of lighting conditions. The cross-domain experiments use information about one set of objects to recognize a similar but different set of objects.