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Similarity preserving multi-task learning for radar target recognition

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ABSTRACT

In this study, a statistical recognition model based on similarity preserving multi-task learning (SP-MTL) is developed for radar target recognition of high-resolution range profile (HRRP) data. A similarity preserving constraint, which describes the similarity information of HRRP samples, is introduced into multi-task learning to enhance the discriminative capability of the statistical model with limited training data. In addition, the SP-MTL model can be applied to the model prediction of new data based on transfer learning theory. Experiments on measured data show that the proposed model can achieve better recognition performance than traditional methods when training data is small. The application of the SP-MTL model to model prediction based on transfer learning theory can improve the learning precision of the new statistical model compared with the single-task learning of new data.

1. Introduction

The work in radar automatic target recognition (RATR) area, according to the employment of the type of wideband radar signals, mainly focuses on high-resolution range profile (HRRP) recognition [5,6,10,14] and synthetic aperture radar (SAR) image or Inverse SAR (ISAR) image recognition [17,19,28,32,33]. A HRRP is composed of an amplitude of coherent summations of complex returns from target scatterers in each range cell, which contains abundant geometric structure information of the radar target, such as target size and scatterer distribution, on the radar target. Compared with the SAR and ISAR images, the HRRPs have been extensively studied and successfully applied to the RATR area with the property of easy acquisition and processing.

Several studies [6,10] have shown that the statistical recognition method is an important and efficient approach for RATR. Target-aspect sensitivity must be considered [9,12] when the HRRP is applied to statistical recognition. Therefore, a subset of multi-aspect HRRPs is collected from a target-aspect sector roughly without the motion through range cells (MTRC) of scatterers to address the abovementioned problem. Each subset from different target-aspect sectors is defined as an aspect-frame of the target, and a statistical model is developed for each aspect-frame [10]. The target membership of a measurement HRRP sample $\mathbf{x}$ is determined based on the posterior probabilities of all frames for all target memberships $\{p(c, m|\mathbf{x})\}_{c=1,m=1}^{C,M_c}$, where c denotes the target membership, C denotes the number of targets, m denotes the frame membership, and M_c denotes the number of frames for target c. In accordance with the Bayesian paradigm, $p(c, m|\mathbf{x}) \propto p(\mathbf{x}|c, m)p(c,$

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m), where $p(\mathbf{x}|c, m)$ is the frame-conditional likelihood of the mth frame for target c, and $p(c, m)$ is the prior frame probability. Prior frame probability is typically assumed to be uniformly distributed. Consequently, an estimation precision of the frame-conditional likelihood significantly affects the performance of statistical recognition.

Several parametric statistical models have been developed to describe the frame-conditional likelihood of the HRRP data, such as Gaussian model [15], Gamma model [6], the two distribution compounded model comprising Gamma distribution and Gaussian mixture distribution [10], subspace approximation model [8], probability principal components analysis (PPCA) model [8,27], and factor analysis (FA) model [25]. Ref. [8] indicated that the FA model can precisely describe the statistical characteristics of the HRRP samples, thereby achieving favorable performance in statistical recognition.

However, complicated statistical models with many unknown parameters, such as the FA model, typically require a multitude of training data. In practice, collecting sufficient training data from each target-aspect in each target is difficult due to the sampling rate limitation. Subsequently, the learning precision of statistical models cannot be fully guaranteed, thus weakening recognition performance. Therefore, improving the recognition performance of statistical models with small-sized training data is critical. Multi-task learning (MTL), which is the sharing of structural elements or parameters among all related tasks, was applied in studies [18,31]. A MTL mechanism improves the estimation accuracy of parameters for each task by reducing the number of parameters to be estimated. Ref. [9] proposed a hidden Markov model (HMM)-based MTL algorithm for real HRRP data; the structure of this algorithm can avoid the requirement of large training data. However, the HMM algorithm, as a statistical model for sequence data, for a HRRP sample in [21] requires calculating state transition probabilities and emission likelihoods across range cells to derive the frame-conditional likelihood for this sample. Therefore, the computational speed during the test stage is relatively slower in the HMM than in other statistical models [6,8,10,15,25,27]. In addition, a FA-based MTL (MTL-FA) model for the HRRP data was developed in [11]. In MTL-FA model, a statistical model is developed for each frame and all frames sharing the same loading matrix and inferring different latent factors. Although MTL-FA model is superior to certain conventional statistical models, it still faces some challenges with limited training data. The MTL-FA model cannot achieve a satisfactory recognition performance when the number of training samples per frame is less than 70, as revealed in experiments on measured data in Section 4.4 of this study.

A similarity preserving (SP) constraint is introduced into the MTL-FA model to enhance the discriminative capability of learned statistical models with small-sized training data. Through the SP constraint, reconstruction samples within the same target remain similar, whereas the reconstruction samples for different targets are required to be more different. The Kullback–Leibler (KL) distance between two data distributions is inversely proportional to the average similarity of samples in the two datasets; therefore, the discriminative capability of the learned statistical models can be improved by constraining similarity information. Thus, the proposed MTL-FA with SP constraint, which is referred to as the SP-MTL model in this study, can not only reduce the dependence of learning precision on training data size but also improve the discriminative capability of the learned statistical models.

Another contribution of this paper is that the SP-MTL model can also be applied to the model prediction of new data based on transfer learning theory. For small amounts of data obtained from unknown aspect-frames of an existing target or a new target in real time, we prefer to utilize the knowledge from learned statistical models of original training data to assist in the model prediction of new data. In recent years, transfer learning has emerged as a new framework that is aimed at helping to improve the learning of the predictive function of a target task using knowledge from the source task [[2,22]. On the basis of Transfer Learning Theory in this study, we transfer the knowledge of shared model parameters to construct new statistical models of new data observed in real time.

In this paper, we propose a HRRP target recognition method based on the SP-MTL model. Experiments on measured data show that the proposed SP-MTL model can achieve better recognition performance than traditional methods when size of the training data is small. In addition, compared with Single-Task Learning (STL) of new data, applying the SP-MTL model on transfer learning-based model prediction can improve the learning precision of new statistical models.

The rest of this paper is organized as follows. The FA model is reviewed in Section 2.1. Then, the proposed FA-based SP-MTL model is introduced in Section 2.2. The inference of the proposed model and classification scheme is derived in Sections 3.1 and 3.2, respectively, followed by presenting the model prediction based on transfer learning theory in Section 3.3. The experimental results of the measured HRRP data are presented in detail in Section 4. Lastly, the conclusion of this study is presented in Section 5.

2. Bayesian model construction

2.1. Review of the FA model

The FA model [25] is a probabilistic generative model that depicts high-dimensional observations distributed in low latent subspaces. A previous work [8] used the FA model to describe the statistical characterization of real HRRP samples. The subset of multi-aspect HRRPs was collected from a target-aspect sector roughly without the MTRC of scatterers due to the target-aspect sensitivity mentioned in Section 1. Each subset of different target-aspect sectors was defined as an aspect-frame of the target. Then, the FA model was developed for each aspect-frame with distinct parameters. The generative model for the ith D-dimensional HRRP sample in the mth frame for target c, where $i \in \{1, ..., N_m\}$ with N_m denotes the number of the HRRP samples in this frame, $m \in \{1, ..., M_c\}$ with M_c denotes the number of frames for target c, and $c \in \{1, ...C\}$ with C