Discriminative Transfer Learning for DrivingPattern Recognition in Unlabeled Scenes

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Abstract

Driving pattern recognition based on features, such as GPS, gear, and speed information, is essential to develop intelligent transportation systems. However, it is usually expensive and labor intensive to collect a large amount of labeled driving data from real-world driving scenes. The lack of a labeled data problem in a driving scene substantially hinders the driving pattern recognition accuracy. To handle the scarcity of labeled data, we have developed a novel discriminative transfer learning method for driving pattern recognition to leverage knowledge from related scenes with labeled data to improve recognitionperformance in unlabeled scenes. Note that data from different scenes may have different distributions, which is a major bottle- neck limiting the performance of transfer learning. To address this issue, the proposed method adopts a discriminative distribution matching scheme with the aid of pseudolabels in unlabeled scenes. It is able to reduce the intraclass distribution disagreement for the same driving pattern among labeled and unlabeled scenes while increasing the interclass distance among different patterns. Pseudolabel in unlabeled scenes are updated iterativelyvia an ensemble strategy that preserves the data structure while enhancing the model robustness. To evaluate the performance of the proposed method, we conducted comprehensive experiments on real-world parking lot datasets. The results show that the proposed method can substantially outperform state-of-the-art methods in driving pattern recognition.

Index Terms—*Driving pattern recognition, interclass separability, intraclass compactness, maximum mean discrepancy(MMD),transfer learning.*

I. INTRODUCTION

RECENTLY, driving pattern recognition, that is, identifying specific movements of cars, such as driving in a lane, turning left, parking, etc., has been extensively studied given its critical importance for self-driving vehicles and intelligent transportation systems. The driving status, such as GPS, gear, and speed information, is important and can be used for driving pattern recognition, but it may be highly variable depending on driving scenes such as different parking lots in Fig. 1. Hence, massive labeled data are often required for accurate driving pattern recognition. However, it is almost impossible to collect sufficient labeled driving data from everydriving scene in practice. Consequently, driving pattern recognition for unlabeled scenes becomes a challenging problem of central importance. It is generally assumed that each driving pattern, such as turning left should be highly correlated across related scenes, despite their large disagreements in distribution.Thus, driving information learned from labeled scenes can be helpful for general driving pattern recognition. Motivated by
the success of transfer learning, which infers labels in an unlabeled target domain by leveraging knowledge from auxiliary domains, we focus on effectively using information fromlabeled driving scenes to enhance driving pattern recognition for the myriad of the unlabeled scene.

As previously mentioned, an obvious obstacle for transfer learning efficacy is the distribution discrepancy among data collected from different scenes. Consider parking lot data[1] as an example, where a dataset records vehicle statuses from dif- ferent parking lots at different instants. As shown in Fig. 1, there are many types of parking lots with varying structures, and driving data considerably vary due to different road lay- outs and other conditions. To illustrate this point, Fig. 2 was generated by the random selection of 10 000 samples from different parking lots, and shows the distributions of two important features, namely, vehicle speed and steering wheel angle, to perform pattern recognition on an identical scenario of driving along a straight line. The data distribution andfeature values poorly agree, showing the diversity of driving features according to the scene, which is one of the major bottlenecks that hinders transfer learning.

Successful transfer learning highly depends on reducing discrepancy in data distributions for the same driving pattern appearing in different scenes while preserving the

Fig. 1.Different driving scenes (e.g., parking lots with varying structures).

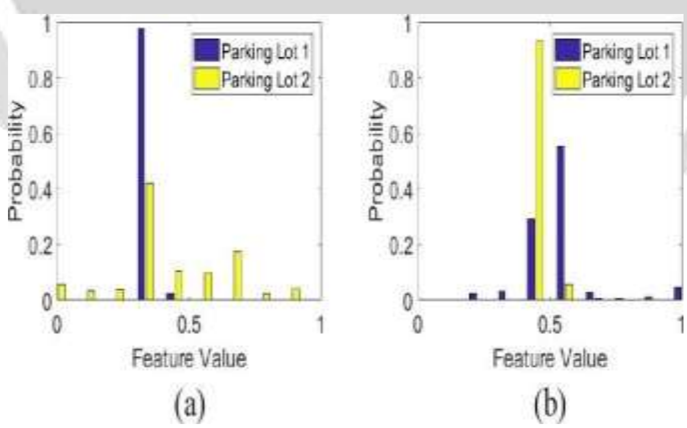


Fig. 2. Distributions of (a) vehicle speed and (b) steering wheel angleaccording to two parking lots are different.

original data structure. Several methods have been recently proposed to discover common feature representations while preserving important properties from original data over differet domains. However, these methods consider global distributions across all the samples, failing to account for the group structure belonging to different labels. In addition, it is not possible to evaluate intraclass disagreement in distributions for an unlabeled target domain unless pseudolabels are assigned, for which pseudolabels have been commonlyemployed. Pseudolabels are usually generated using conventional classifiers beforehand to guide data preprocessing for transfer learning, while the generated pseudolabels are not updated during transference. Moreover, these methods mainly consider the intraclass discrepancy, neglecting the dispersion across classes. In many challenging real problems, the performance of these classifiers is unsatisfactoryand unreliable pseudolabels are thereby obtained, given the large discrepancy in distributions, undermining the effectiveness of transfer learning. A more suitable approach should gradually refine the pseudolabels by incorporating knowledge from labeled domains along with the transfer learning process. The refined labels may then provide more accurate group information in the target domain, enhancing the transferlearning efficacy.

To tackle all these issues and improve the transfer learning performance, we developed the proposed framework, discriminative transfer learning (DTL). The source and target dataare projected onto a common space via discriminative transfermatching to enhance intraclass compactness, that is, affinity

within the same class, and interclass separability, that is, dispersion among different classes. And then the majority voting method is used to iteratively refine the pseudolabels of target data. The proposed framework is illustrated in Fig. 3. The maincontributionsof this article can be summarized as follows.

1) DTL develops a novel transfer learning technique to address the driving pattern recognition problem for unlabeled scenes.
2) The proposed method incorporates the discriminative distribution matching which enhances intraclass compactness and interclass separability to reduce the discrepancy in distributions, that is, one of the bottleneck problems of transfer learning.
3) DTL iteratively refines the pseudolabels using an ensemble classifier to preserve the original data structure and enhance the DTL.a

The remainder of this article is organized as follows. First, we briefly review the related work in Section II. The detailed design and implementation of DTL are provided in Sections III and IV, respectively. Section V presents the performance of DTL compared to state-of-the-art methods. Finally, we draw conclusions in Section VI.

1. RELATED WORK

As we intend to apply transfer learning to driving pattern recognition, we briefly discuss the existing related methods. Transfer learning is inspired by the human ability to apply previous knowledge in different situations to solve new problems.

It has achieved remarkable success in a wide range of applications, including text sentiment classification; image classification; human activity classification; software defect classification; and multilanguage text classification. Compared to traditional learning, transfer learning has a bottleneck regarding thediscrepancy in data distributions between the source and targetdomains. Consider driving pattern recognition as an example. The driving status data are recorded in various scenes and under distinct conditions, usually leading to distinct data distributions. Thus, transfer learning should reduce the discrepancy among data distributions.

Remarkable research efforts have been devoted to unifydata representation from different domains and thus improve the agreement among distributions while preserving important properties from the original data. For instance, the discriminative deep multimetric learning method jointly learns multiple neural networks to characterize the correlation among different domains. Sharable and individual multi- view metric learning seeks for an individual distance metric for each view and a shared representation for different views. Note that these two methods were developed based on supervised information of similar and distinct pairs. Transfer component analysis (TCA) learns the transfer components across domains using the maximum mean discrepancy (MMD),a common measure of the difference among domains. Transfer joint matching(TJM) aims to enhance the agreement in data distributions by jointly matching features and reweighting the instances across domains. Geodesic flow kernel (GFK)

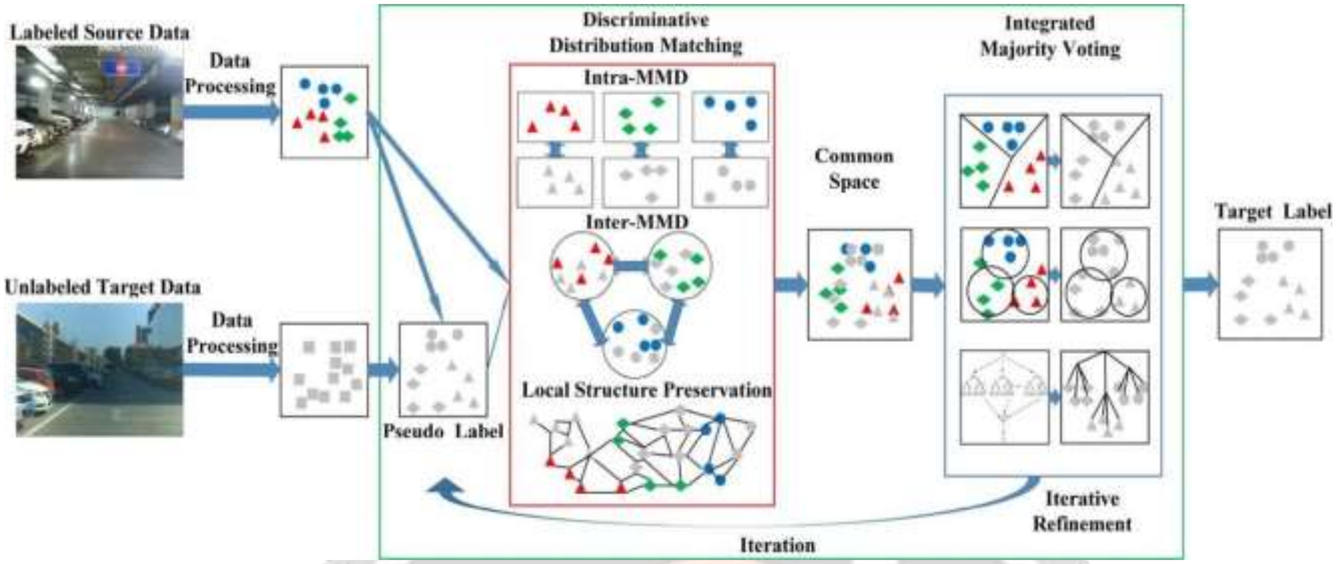


Fig. 3. Framework of the proposed DTL method. Source and target data can be projected onto a common space by the discriminative distribution matching, which can reduce the MMD within classes, increase the distance across classes, and preserve the local manifold structure. Then, the majority voting classification based on source data can be used to iteratively refine the labels of target data.

exploits low-dimensional structures and integrates differentdomains. Correlation alignment (CORAL) minimizes thedomain shift by aligning the second-order statistics fromsource to target distributions. Moreover, landmarks-based kernelized subspace alignment (LSA) aims to select important landmarks in data and perform subspace alignment forinterdomain discrepancy reduction. Domain adaptive neuralnetworks (DANNs) use simple neural-network models fordomain adaptation in object recognition. They incorporate theMMD as regularization in the supervised learning process toreduce distribution disagreement between the source domainsand target domain in the latent space. Although these transfer learning methods focus on enhancing the agreement inglobal data distributions between the source domains and target domain, they neglected the group structure and mixed dataof different labels, leading to the global domain shift. According to .features from data samples with the same label across different domains should lie on a common subspace, called latent space or submanifold. Therefore,the agreement in intraclass distributions should be enforcedfor data from different domains to prevent the global domainshift. To this end, pseudolabels of samples in the targetdomain can be defined. Existing methods often rely on pseudolabels obtained by conventional classifiers. For instance,joint distribution adaptation (JDA) and balanced distribution adaptation (BDA) jointly adopt both the marginaland conditional distributions based on predicted pseudolabels.Adaptation regularization-based transfer learning (ARTL)employs the MMD as a distance measure to perform marginaldistribution adaptation. Manifold embedded distribution alignment (MEDA) learns dynamic distribution alignment toquantitatively account for marginal and conditional distributions. Joint geometric and statistical alignment (JGSA) projects source and target domain data onto two subspaces, where the geometric shift and distribution shift are simultaneously reduced. Stratified transfer learning (STL)obtains pseudolabels for the target domain via majority voting. They generate pseudolabels before transfer learning, completely relying on conventional classifiers employed before data adaptation between different domains. The moving semantic trans-fer network (MSTN) employs the AlexNet architecture while the centroid alignment is performed for deep features to reduce the discrepancybetween the source domain and target domain.

However, these methods mainly consider the intraclass dis- crepancy, neglecting the dispersion across classes. The joint and discriminative domain adaptation (JDDA) method takes advantage of the ResNet architecture, and focuses onthe intraclass compactness and interclass separability of the source domains only. As both the source domains and tar-get domain are expected for domain adaptation, the adequate data alignment could further improve learning efficacy. The consideration motivates the proposed DTL to alternativelyand iteratively update pseudolabels and adapt inter- and intra- MMD on both the source and target domains to obtain better transfer learning performance.

1.DRIVING PATTERN RECOGNITION

In this section, we introduce the proposed DTL framework. First, we define the problem and describe the main idea of DTL. Then, the three major steps of DTL are detailed, namely,discriminative distribution matching, pseudo label prediction, and iterative refinement.

A. Problem Statement

DTL transfers knowledge from labeled samples in a source domain to identify the patterns among samples in a target domain without label information. More specifically, domain D is composed of an m-dimensional feature space X and

C-cardinality label set Y, where $\mathbf{x} \in X$ is a sample and

domains.

EXPERIMENTS AND EVALUATION

We conducted extensive experiments on driving pattern recognition to evaluate the proposed DTL approach. A. Data Preparation We applied the proposed DTL to identify driving patterns in different parking lot scenes. The detailed data collection and preprocessing steps are summarized in the following.

1) Data Collection: The driving data were collected from different parking lots with distinct structures and road conditions. Each vehicle for data acquisition was equipped with several sensors, as shown in Fig. 5. The data attributes include Frame ID, Turn Light, Vehicle Speed, Steering Wheel, Brake, Brake Information, Engine Speed, Accelerated Speed, Gear, Mileage, Oil Consumption, Date Time, Longitude, Latitude, Altitude, Angle, and GPS Speed. We aimed to recognize the 16 different driving patterns listed in Table II. Five datasets were collected from five parking lots A–E collecting 10 047, 9157, 8924, 9765, and 8436 samples, respectively. As shown in Fig. 1, different parking lots have very different data distributions, increasing the divergence between the source and target domains.

2) Data Preprocessing: Based on the original data, we performed preprocessing before adapting the proposed DTL framework for driving pattern recognition. From 36 attributes in the original data, we selected 13 while removing those highly correlated among all instances in one or more domains, as they do not add discriminative information. Then, the selected attributes were encoded for subsequent processing. For instance, character attributes, such as Gear with possible states D, N, N/A, and R, were represented using one-hot encoding. Feature wise normalization was then performed for each dataset individually. The datasets from different parking lots have distinct distributions, as shown in Fig. 2. Hence, each dataset from one parking lot was considered as belonging to one scene (domain). To investigate more detailed information during knowledge transfer for driving scenes, we applied DTL to two scenarios, either one or multiple sourcedomains. We use notation

Fig. 4. Driving status features.

DRIVING PATTERNS IN PARKING LOT DATASETS

Class	Pattern
1	Driving in lane outside parking lot
2	Going straight at intersection outside parking lot
3	Turning left at intersection outside parking lot
4	Turning right at intersection outside parking lot
5	Entering parking lot
6	Driving in lane looking for parking spot
7	Going straight at intersection looking for parking spot
8	Turning left at intersection looking for parking spot
9	Turning right at intersection looking for parking spot
10	Parking
11	Leaving parking spot
12	Driving in lane looking for exit
13	Going straight at intersection looking for exit
14	Turning left at intersection looking for exit
15	Turning right at intersection looking for exit
16	Leaving parking lot

A. Comparison Methods

We compared the proposed DTL approach to 17 classifiers.

1) 1-NN assigns each testing sample to the class most common via its NN.
2) SVM divides the samples of the separate categories by a clear margin that is as wide as possible.
3) RF is an ensemble learning method which constructs a multitude of decision trees and outputs the class with theindividual trees.
4) TCA learns the transfer components across domains using MMD, then data distributions in different domainsare close to each other.
5) GFK exploits low-dimensional structures and changes the geometric and statistical properties from the source to the target domain.
6) JDA aims to jointly adapt both the marginal distribution and conditional distribution in a dimensionalityreduction procedure.
7) TJM aims to enhance the agreement in data distributions by jointly matching features and reweighting theinstances across domains.
8) ARTL employs the MMD as distance measure to perform marginal distribution adaptation.
9) CORAL minimizes the domain shift by aligning the second-order statistics from source and target distributions.
10) LSA aims to select important landmarks and perform subspace alignment for reducing interdomaindiscrepancy.
11) JGSA projects all data to two subspaces, where the geometric shift and distribution shift are simultaneouslyreduced.
12) BDA can adaptively leverage the importance of the marginal and conditional distribution discrepancies.

13) STL obtains pseudolabels for the target domain via majority voting and then performs intraclass knowledgetransfer.
14) MEDA learns dynamic distribution alignment to quantitatively account for marginal and conditionaldistributions.
15) DANNs uses simple neural-network models for domain adaptation in object recognition.
16) MSTN employs the AlexNet architecture while the centroid alignment is performed for deep features.
17) The instance-based JDDA method takes advantage of the ResNet architecture.

The 1-NN, SVM, and RF classifiers can be considered as conventional methods, whereas the others are transfer learning approaches. They aim to reduce the difference between the source and target domains. Then, they train the classifier on the labeled source data, and test it on the unlabeled target data. The codes for the comparison methods areavailable online.

B.Evaluation

Under our experimental setup, the optimal parameters cannot be obtained using cross-validation, as labeled and unlabeled data are sampled from different distributions. Thus, we evaluated all methods by heuristically searching the parameter space for the optimal settings and report the best results for each method. We used the widely used classification accuracy on test data as evaluation measure

Accuracy = |xj : xj ∈ Dt ∧ ˆyj = yj| |xj : xj ∈ Dt|

where Dt is the set of test data, yj is the truth label of xj, and yˆj is the label predicted by the classification algorithm. We executed each algorithm ten times with different random initializations and obtained the average results.

D. Results and Analysis

1) Effectiveness of Intraclass and Interclass Transference: To verify the effectiveness of DTL from the distribution

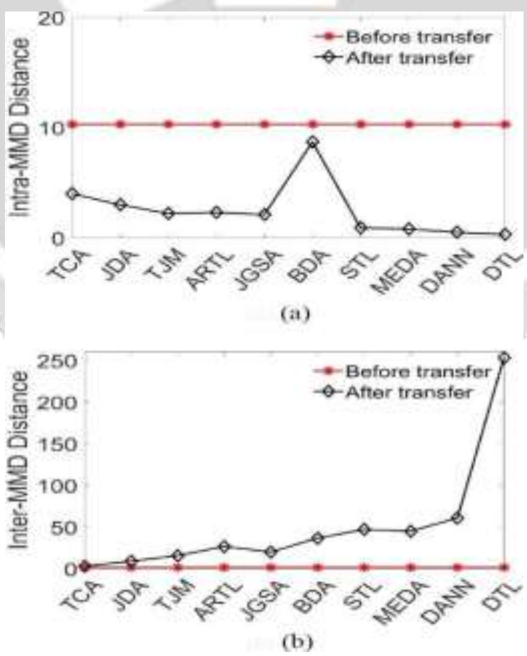


Fig. 5. Intra-MMD and (b) inter-MMD of all samples on the dataset ACDE → B.

distance, we compared it to nine methods that can reducethe MMD between source and target domains. Take the *ACDE B* dataset as an example. The intra-MMD and inter-MMD of all methods are shown in Fig. 5. In addition, the*t*-

distributed stochastic neighbor embedding of all data points before and after transformation is depicted in Fig. 6(a),(b),respectively. " " and " " represent data from *ACDE* and *B*, and different colors represent different classes. Points in the same class from

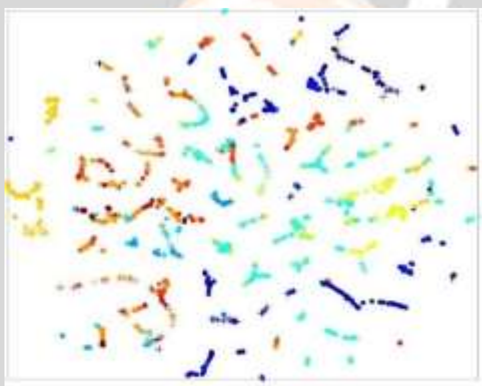
different domains become closer after transformation. Compared with other methods, DTL can sub- stantially reduce the discrepancy between the source and targetdomains, and increase the interclass distance, because DTL reduces the difference within

each category and iteratively refines the pseudolabels using the ensemble strategy.

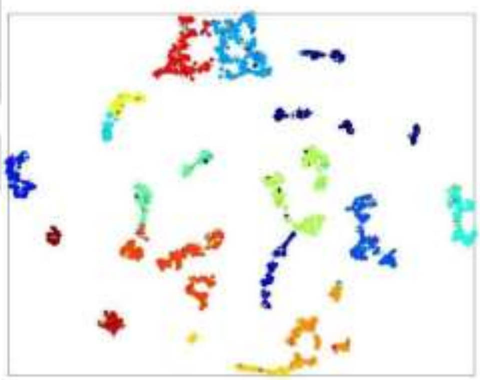
To illustrate the interclass discrepancy reduction using DTL,the intra-MMD and accuracy are listed in Table III. Most intra-

MMD values are reduced by DTL, and the classifica-tion performance improves. In addition, the inter-MMD for TCA, JDA, STL, and DTL is shown in Fig.7. Compared with other methods, most of the values of DTL increase. By iteratively updating the pseudolabels using the ensem-ble method, DTL can reduce the intraclass divergence and increase the interclass distance at every iteration to improve the classification performance.

To verify the effectiveness of DTL by embedding similarity,we computed the 10-NN similarity matrix on embedding $A^T X$ obtained from DTL. To better demonstrate the results, we onlyselected four classes and 25 samples per domain. The first 100 samples and the last 100 samples comprised the source and

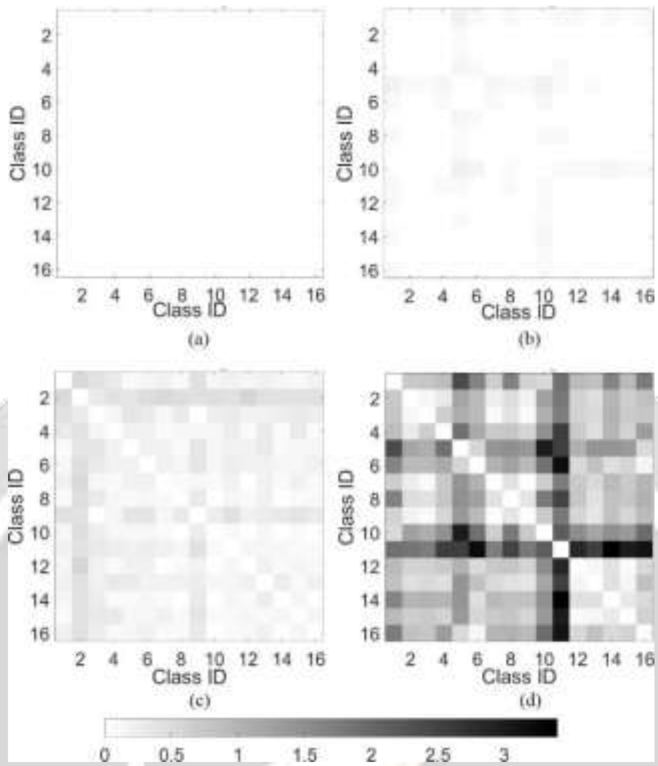


(a)

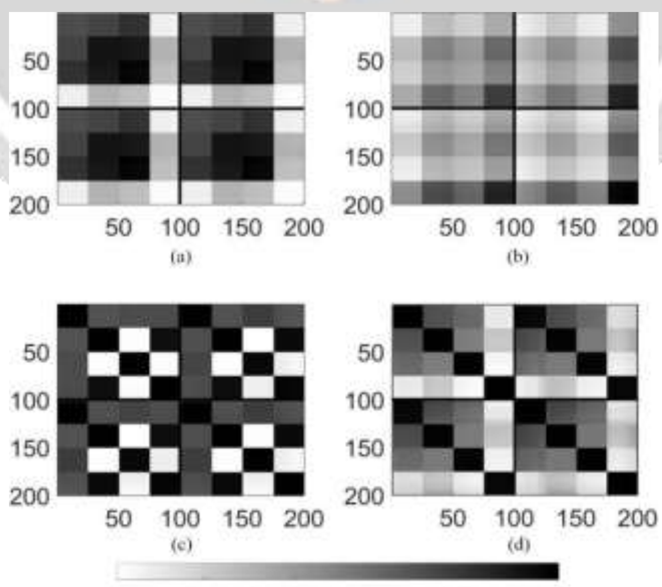


(b)

Fig. 6. (a) Data visualization before transformation (intra-MMD, 10.3; inter- MMD, 1.6). (b) Data visualization after transformation (intra-MMD, 0.3; inter- MMD, 253.3) on the dataset *ACDE* *B*. " " and " " represent the source and target domains, respectively, different colors represent different categories.



target domains, respectively. We also constructed the similaritymatrices for TCA, JDA, and STL using their optimal param- eter settings. The similarity matrices are depicted in Fig. 9, where the diagonal and anti-diagonal blocks indicate intraclasssimilarity within and across domains, respectively, whereas the other blocks indicate interclass similarity. DTL achieves higher intraclass and lower interclass similarity both within and across domains.



1) *Parameter Sensitivity:* The DTL approach involves three model parameters: 1) number k of subspace bases;
2) Laplacian regularization parameter β; and 3) interclass regularization parameter α. We conducted a

sensitivity anal- ysis to validate the DTL optimal performance under sev- eral parameter values. We randomly selected *A D*,*D B*, and *ACDE B* to illustrate the parameter sen- sitivity analysis. We observed similar trends on all other datasets but do not report their results here due to space constraints.

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Hyperparameter tuning is commonly needed in many other state-of-the-art methods. For instance, JDA [12] and STL [17]used as benchmarks in this article have parameters ($p$subspacebases and regularization parameters) that need to be adjustedin order to achieve optimal performance. Similar to the com- pared methods, we ran DTL while varying k, β, and α, and obtained the classification accuracy according to the different values, as shown in Fig. 10. To demonstrate that our modelcan achieve optimal performance under varying parameter values, the best results of other comparison methods are depicted as dashedlines. From Fig. 10(a), we chose k [8, 13] forour experiments. Fig. 10(b) shows the classification accuracy according to the Laplacian parameter β, where the Laplacian constraint results useful to retain the local manifold structure in DTL, and our model generally outperforms the other methods in a wide $\in$ range β [10^{-6}, 10^{-1}]. Fig. 10(c) shows the classification accuracy according to interclass regularization parameter α, where the inter-MMD should be increased. Again, our model outperforms the comparison methods in a wide range $\alpha \in [10^{-7}, 10^{-2}]$.

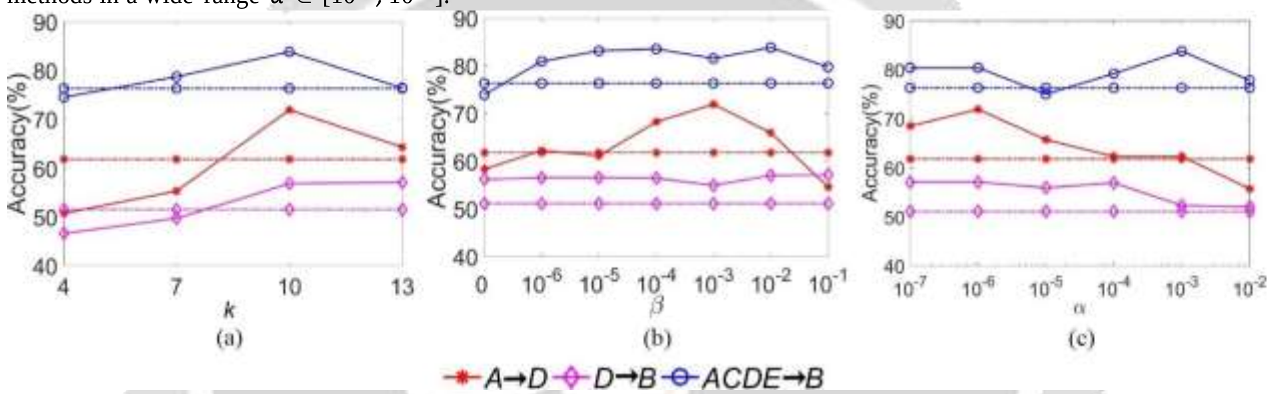

Fig. 9. Parameter sensitivity of DTL on three datasets (dashed lines indicate the best results from comparison methods). (a) $p$subspace bases k. (b) Laplacianregularization parameter β. (c) Interclass regularization parameter α.

We expect it is possible to perform hyperparameter tuning for the proposed method given a real-word dataset. Similarto the setup in our experiments, we should be able to tunethe hyperparameters based on the performance in the source domain. A similar strategy has also been applied to adjust hyperparameters in [34] and [43]. For example, we com- pare the parameter sensitivity of k from A to other domains$A$ B, A C, and A D. As shown in Fig. 11, we observe the trends of performance in the source and target domains with respect to different hyperparameter selections are consistent with each other, we are comfortable to use validation performance in the source domain as an indicator of performance in the target domain in the hyperparameter tuning process.

CONCLUSION

In this article, we have proposed a driving pattern recognition method based on DTL. It aims to adjust intraclass and interclass distributions through an iterative ensemble propcedure to enhance the compactness (i.e., reduce intraclass discrepancy) and separability (i.e., increase interclass distance)of transfer learning. Extensive experiments show that DTL is effective and robust for driving pattern recognition and can significantly outperform various state-of-the-art methods on parking lot datasets. We mainly focused on the transfer learning framework for driving pattern recognition in this article. More effective ensemble methods can be considered to integrate classification results from different classifiers and furtherimprove the recognition accuracy, which will beone of our future works.

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