

# Manifold Criterion Guided Transfer Learning via Intermediate Domain Generation

流形标准引导的迁移学习：通过中间域生成实现

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Transactions on Neural  
Networks and Learning  
Systems》



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# 01 背景介绍



# 背景介绍

- 1、什么是迁移学习
- 2、迁移学习的相关研究工作及其思想
- 3、本文方法体现了哪些思想和创新

## 什么是迁移学习

### 迁移学习

一种能够利用在一个任务或领域上学到的知识来帮助完成另一个相关但不同的任务或领域的机器学习方法。

### 为什么迁移

- 1、源域和目标域**不满足独立同分布**。
- 2、目标域数据标注困难，数据集难以获取。

### 域适应技术

迁移学习的一个重要分支，专注于解决源域与目标域之间**数据分布不一致**的问题。



图1 无背景的图像向有背景的图像迁移

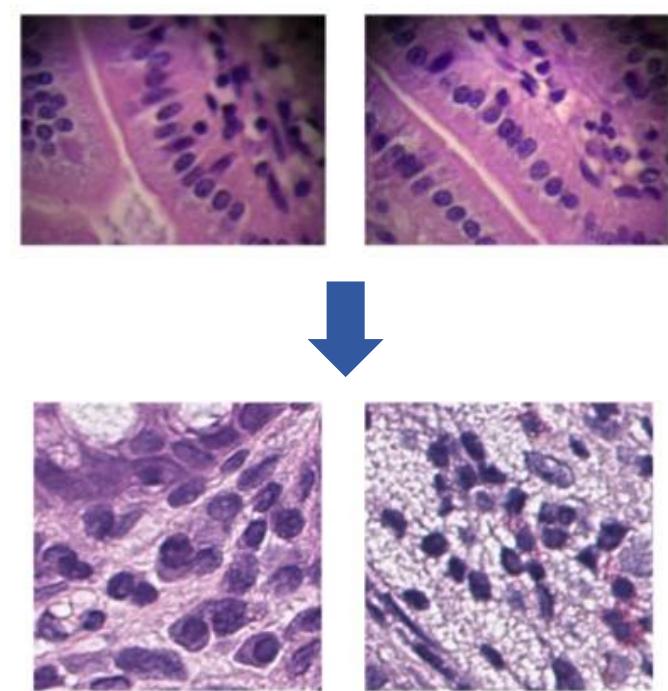


图2 计算机辅助诊断中老鼠组织图像向人体结肠组织图像迁移

## 迁移学习相关研究

### 基于特征增强/变换的方法

核心思想是通过改变或调整数据的特征表示形式，减少域间差异。这种方法侧重于找到一个中间的表示空间。

- Li等人提出了一种异构特征增强方法，旨在为领域适应(DA)学习一个转换后的特征空间[1]。
- Gopalan等人提出了一种无监督方法(SGF)，用于低维子空间转移[2]。

#### 参考文献：

[1] W. Li, L. Duan, D. Xu, and I. W. Tsang, "Learning with augmented features for supervised and semi-supervised heterogeneous domain adaptation," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 36, no. 6, pp. 1134–1148, Jun. 2013.

[2] R. Gopalan, R. Li, and R. Chellappa, "Domain adaptation for object recognition: An unsupervised approach," in *Proc. ICCV*, Nov. 2011, pp. 999–1006.

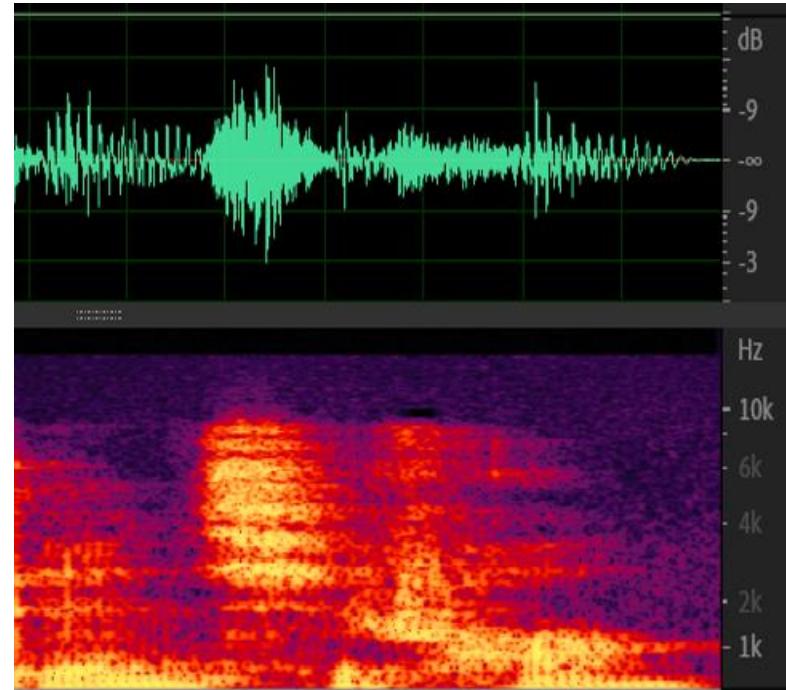


图1 关于空间变换的一个例子，时域空间向频域空间转换

## 迁移学习相关研究

### 基于特征表示的方法

#### 浅层域适应方法介绍

核心思想是学习一个或一系列能够跨越不同领域的**共有特征表示**，这种方法侧重学习对领域变化具有鲁棒性的特征。

- Jhuo等人提出了一种利用低秩建模的鲁棒域适应方法，其中源域数据通过目标域进行重构[3]
- Shao等人提出了一种潜转移子空间学习（LTSI）方法，首先预学习一个子空间，随后构建跨域的低秩表示模型[4]。

#### 参考文献：

- [3] I.-H. Jhuo, D. Liu, D. Lee, and S.-F. Chang, “Robust visual domain adaptation with low-rank reconstruction,” in Proc. CVPR, Jun. 2012, pp. 2168–2175.
- [4] M. Shao, D. Kit, and Y. Fu, “Generalized transfer subspace learning through low-rank constraint,” Int. J. Comput. Vis., vol. 109, nos. 1–2, pp. 74–93, 2014.



图1 关于域不变特征的一个例子

## 深度迁移学习

- Long等人[5]提出了深度适应网络 (DAN) 方法，通过在跨域的**高层特征**上施加最大均方差 (MMD) 损失来实现。
- Long等人[6]还提出了一种残差迁移网络 (RTN)，倾向于基于softmax损失学习残差分类器。

### 参考文献：

- [5] M. Long, Y. Cao, J. Wang, and M. Jordan, “Learning transferable features with deep adaptation networks,” in Proc. ICML, Feb. 2015, pp. 97–105.
- [6] M. Long, H. Zhu, J. Wang, and M. I. Jordan, “Unsupervised domain adaptation with residual transfer networks,” in Proc. NIPS, 2016, pp. 136–144.

### MMD的介绍

最大均值差异 (MMD) 是一种衡量两个概率分布之间差异的方法，用来评估源域和目标域之间的相似性或差异性。

$$MMD^2(F, p, q) = \sup_{f \in F} \|E_{x \sim p}(f(x)) - E_{y \sim q}(f(y))\|^2$$

其中， $p$ 、 $q$ 表示两个待度量的概率分布， $F$ 表示函数类， $\sup$ 代表求上界， $f$ 表示映射函数。

当使用映射函数 $\phi$ 将源域和目标域数据集从原始空间映射到 $H$ 后 MMD函数可以表示为：

$$MMD^2(\mathbf{X}_S, \mathbf{X}_T) = \left\| \frac{1}{n_s} \sum_{i=1}^{n_s} \phi(x_{s_i}) - \frac{1}{n_t} \sum_{j=1}^{n_t} \phi(x_{t_j}) \right\|_H^2$$

## 本文方法的创新

- 提出了一种无监督的**流形准则生成迁移**学习方法。通过**局部**生成差异度量 (LGDM) 实现**局部转移的有效对齐**。
- 提出了**全局**生成差异度量 (GGDM) 确保了领域间**局部和全局亲和结构的同时保持**。
- 集成了针对转移矩阵Z的LRC正则化，利用**块对角属性**和**低秩约束**防止负面迁移。
- 提出了一种**简化版**MCTL (MCTL-S) 方法。

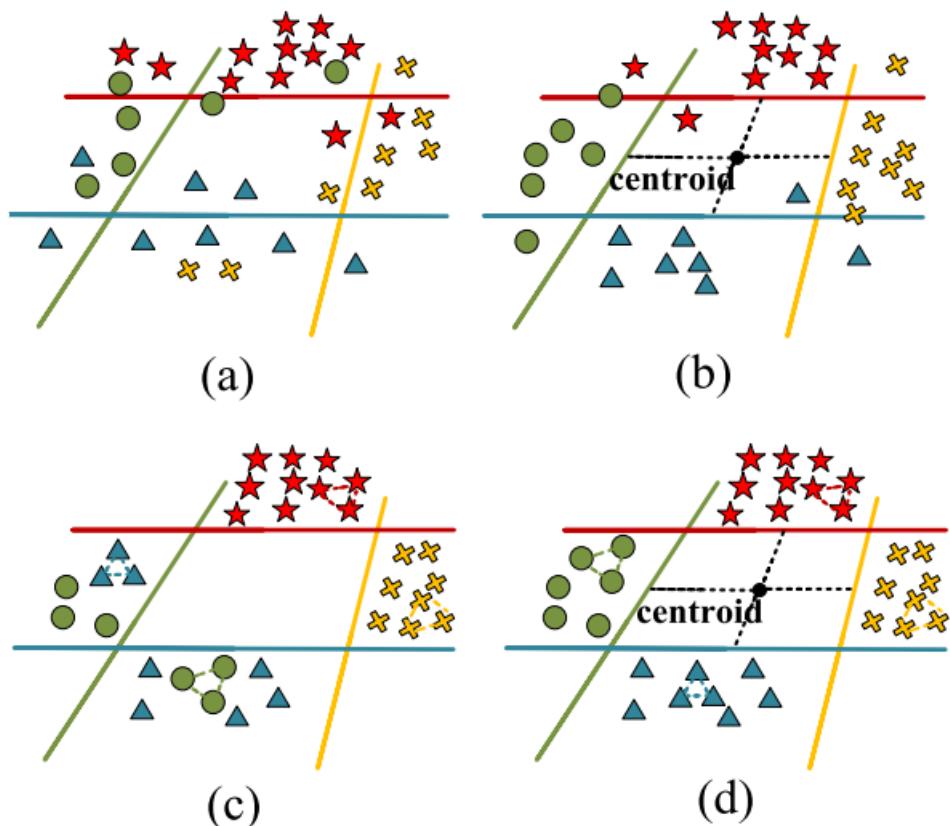


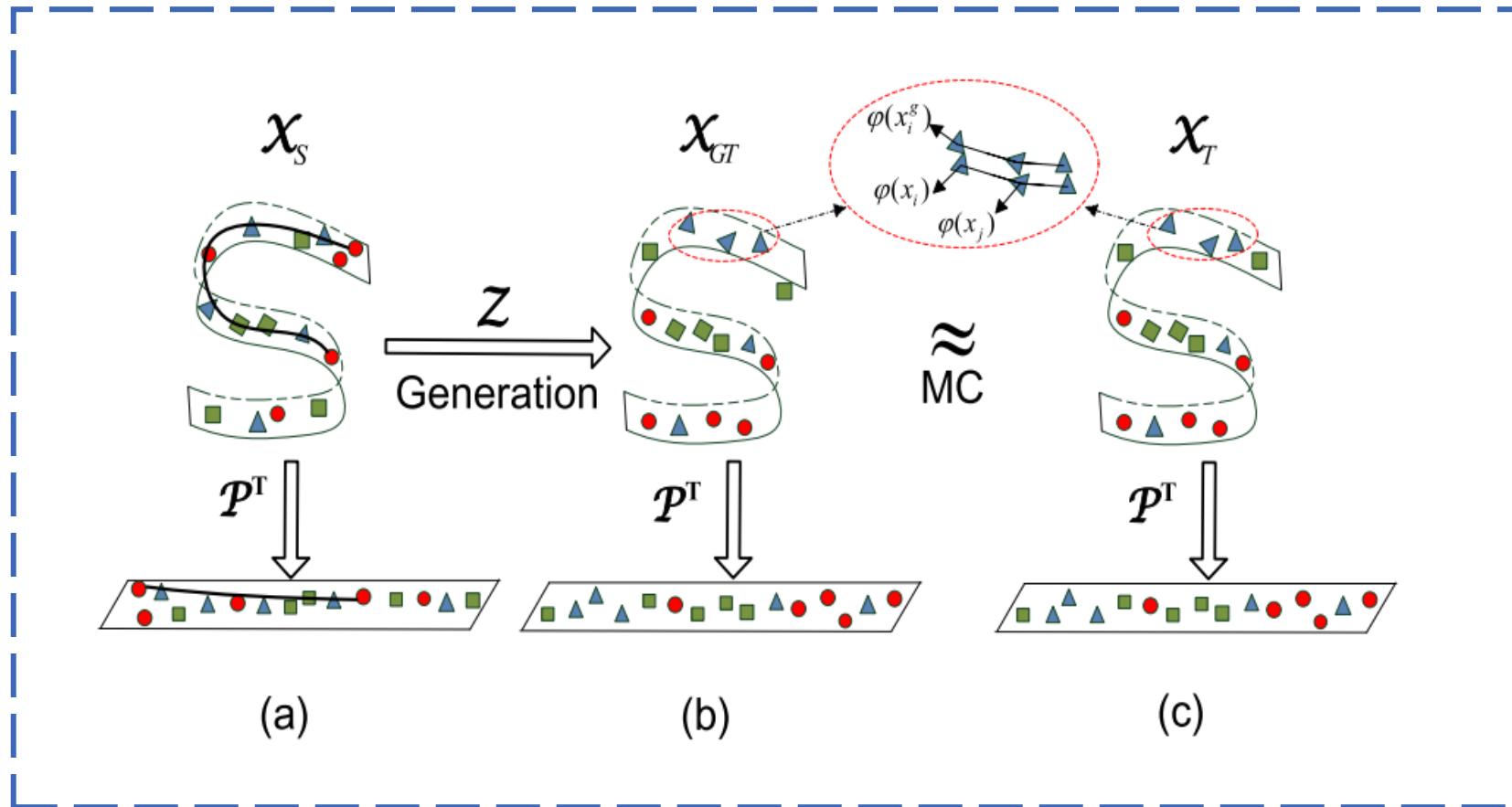
图1 MCTL的动机。线条代表源域的分类边界。质心代表所有数据点的几何中心。

02

# 研究方法



## MANIFOLD CRITERION GUIDED TRANSFER LEARNING



## MANIFOLD CRITERION GUIDED TRANSFER LEARNING

### MC-Based Local Generative Discrepancy Metric

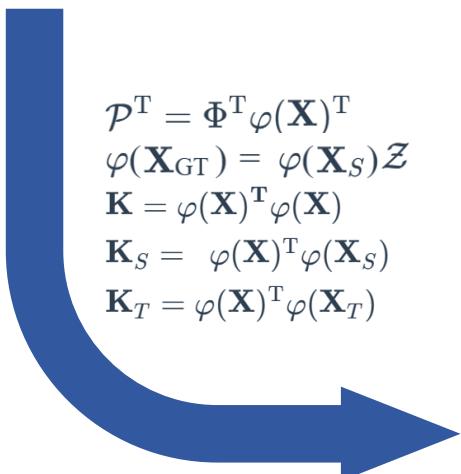
$$\begin{aligned} \text{LGDM}(\mathbf{D}_{\text{GT}}, \mathbf{D}_T) &= \sum_{p,q}^{n_T} W_{pq} \|\varphi(x_{\text{GT}}^p) - \varphi(x_T^q)\|_2^2 \\ &= \text{Tr}(\varphi(\mathbf{X}_{\text{GT}})\mathbf{D}(\varphi(\mathbf{X}_{\text{GT}})^T) \\ &\quad + \text{Tr}(\varphi(\mathbf{X}_T)\mathbf{D}(\varphi(\mathbf{X}_T)^T) \\ &\quad - 2\text{Tr}(\varphi(\mathbf{X}_{\text{GT}})\mathbf{W}(\varphi(\mathbf{X}_T)^T) \end{aligned}$$

$$W_{pq} = \begin{cases} 1, & \text{if } x_{\text{GT}}^p \in NN_k(x_T^q) \text{ or } x_T^q \in NN_k(x_{\text{GT}}^p) \\ 0, & \text{otherwise} \end{cases}$$

$$D_{pp} = \sum_q W_{pq}, p = 1, \dots, n_T. \quad \text{a diagonal matrix}$$

$$\begin{aligned} \text{LGDM}(\mathbf{D}_{\text{GT}}, \mathbf{D}_T) &= \sum_{p,q}^{n_T} W_{pq} \|\varphi(x_{\text{GT}}^p) - \varphi(x_T^q)\|_2^2 \\ &= \text{Tr}(\varphi(\mathbf{X}_{\text{GT}})\mathbf{D}(\varphi(\mathbf{X}_{\text{GT}})^T) \\ &\quad + \text{Tr}(\varphi(\mathbf{X}_T)\mathbf{D}(\varphi(\mathbf{X}_T)^T) \\ &\quad - 2\text{Tr}(\varphi(\mathbf{X}_{\text{GT}})\mathbf{W}(\varphi(\mathbf{X}_T)^T) \end{aligned}$$

$\mathcal{P}^T = \Phi^T \varphi(\mathbf{X})^T$   
 $\varphi(\mathbf{X}_{\text{GT}}) = \varphi(\mathbf{X}_S)\mathcal{Z}$   
 $\mathbf{K} = \varphi(\mathbf{X})^T \varphi(\mathbf{X})$   
 $\mathbf{K}_S = \varphi(\mathbf{X})^T \varphi(\mathbf{X}_S)$   
 $\mathbf{K}_T = \varphi(\mathbf{X})^T \varphi(\mathbf{X}_T)$



$$\begin{aligned} &\min_{\Phi, \mathcal{Z}} \frac{1}{(n_T)^2} \text{Tr}(\Phi^T \mathbf{K}_S \mathcal{Z} \mathbf{D}(\Phi^T \mathbf{K}_S \mathcal{Z})^T) \\ &\quad + \frac{1}{(n_T)^2} \text{Tr}(\Phi^T \mathbf{K}_T \mathbf{D}(\Phi^T \mathbf{K}_T)^T) \\ &\quad - \frac{2}{(n_T)^2} \text{Tr}(\Phi^T \mathbf{K}_S \mathcal{Z} \mathbf{W}(\Phi^T \mathbf{K}_T)^T). \end{aligned}$$

## MANIFOLD CRITERION GUIDED TRANSFER LEARNING

### MC-Based Local Generative Discrepancy Metric

$$\begin{aligned} & \min_{\Phi, \mathcal{Z}} \frac{1}{(n_T)^2} \operatorname{Tr}(\Phi^T \mathbf{K}_S \mathcal{Z} \mathbf{D} (\Phi^T \mathbf{K}_S \mathcal{Z})^T) \\ & + \frac{1}{(n_T)^2} \operatorname{Tr}(\Phi^T \mathbf{K}_T \mathbf{D} (\Phi^T \mathbf{K}_T)^T) \\ & - \frac{2}{(n_T)^2} \operatorname{Tr}(\Phi^T \mathbf{K}_S \mathcal{Z} \mathbf{W} (\Phi^T \mathbf{K}_T)^T). \end{aligned}$$

$$W_{pq} = \begin{cases} 1, & \text{if } x_{\text{GT}}^p \in NN_k(x_T^q) \text{ or } x_T^q \in NN_k(x_{\text{GT}}^p) \\ 0, & \text{otherwise} \end{cases}$$

$$D_{pp} = \sum_q W_{pq}, p = 1, \dots, n_T.$$

### Global Generative Discrepancy Metric Loss

$$\min_{\Phi, \mathcal{Z}} \frac{1}{n_T} \|\Phi^T (\mathbf{K}_S \mathcal{Z} - \mathbf{K}_T) \mathbf{1}\|_2^2$$

where  $\mathbf{1}$  represents a full one column vector.

$$\text{GGDM}(D_{\text{GT}}, D_T) = \frac{1}{n_T} \sum_{i=1}^{n_T} (\varphi(\mathbf{X}_{\text{GT}}^i) - \varphi(\mathbf{X}_T^i))^2$$

$$\begin{aligned} \mathcal{P}^T &= \Phi^T \varphi(\mathbf{X})^T \\ \varphi(\mathbf{X}_{\text{GT}}) &= \varphi(\mathbf{X}_S) \mathcal{Z} \end{aligned}$$

$$\begin{aligned} \text{GGDM}(D_{\text{GT}}, D_T) &= \frac{1}{n_T} \sum_{i=1}^{n_T} \mathcal{P}^T (\varphi(\mathbf{X}_{\text{GT}}^i) - \varphi(\mathbf{X}_T^i))^2 \\ &= \frac{1}{n_T} \|\mathcal{P}^T (\varphi(\mathbf{X}_S) \mathcal{Z} - \varphi(\mathbf{X}_T)) \mathbf{1}\|_2^2 \end{aligned}$$

$$\begin{aligned} \mathbf{K} &= \varphi(\mathbf{X})^T \varphi(\mathbf{X}) \\ \mathbf{K}_S &= \varphi(\mathbf{X})^T \varphi(\mathbf{X}_S) \\ \mathbf{K}_T &= \varphi(\mathbf{X})^T \varphi(\mathbf{X}_T) \end{aligned}$$

$$\min_{\Phi, \mathcal{Z}} \frac{1}{n_T} \|\Phi^T (\mathbf{K}_S \mathcal{Z} - \mathbf{K}_T) \mathbf{1}\|_2^2$$

## MANIFOLD CRITERION GUIDED TRANSFER LEARNING

### MC-Based Local Generative Discrepancy Metric

$$\begin{aligned} & \min_{\Phi, \mathcal{Z}} \frac{1}{(n_T)^2} \operatorname{Tr}(\Phi^T \mathbf{K}_S \mathcal{Z} \mathbf{D} (\Phi^T \mathbf{K}_S \mathcal{Z})^T) \\ & + \frac{1}{(n_T)^2} \operatorname{Tr}(\Phi^T \mathbf{K}_T \mathbf{D} (\Phi^T \mathbf{K}_T)^T) \\ & - \frac{2}{(n_T)^2} \operatorname{Tr}(\Phi^T \mathbf{K}_S \mathcal{Z} \mathbf{W} (\Phi^T \mathbf{K}_T)^T). \end{aligned}$$

$$W_{pq} = \begin{cases} 1, & \text{if } x_{\text{GT}}^p \in NN_k(x_T^q) \text{ or } x_T^q \in NN_k(x_{\text{GT}}^p) \\ 0, & \text{otherwise} \end{cases}$$

$$D_{pp} = \sum_q W_{pq}, p = 1, \dots, n_T.$$

### Global Generative Discrepancy Metric Loss

$$\min_{\Phi, \mathcal{Z}} \frac{1}{n_T} \|\Phi^T (\mathbf{K}_S \mathcal{Z} - \mathbf{K}_T) \mathbf{1}\|_2^2$$

where  $\mathbf{1}$  represents a full one column vector.

### LRC for Domain Correlation Enhancement

$$\|\mathcal{Z}\|_*$$

利用目标矩阵  $Z$  的低秩结构来增强不同领域之间的相关性

## Completed Model of MCTL

$$\begin{aligned} \min_{\Phi, \mathcal{Z}} \quad & \frac{1}{(n_T)^2} \text{Tr}(\Phi^T \mathbf{K}_S \mathcal{Z} \mathbf{D} (\Phi^T \mathbf{K}_S \mathcal{Z})^T) \\ & + \frac{1}{(n_T)^2} \text{Tr}(\Phi^T \mathbf{K}_T \mathbf{D} (\Phi^T \mathbf{K}_T)^T) \\ & - \frac{2}{(n_T)^2} \text{Tr}(\Phi^T \mathbf{K}_S \mathcal{Z} \mathbf{W} (\Phi^T \mathbf{K}_T)^T) \\ & + \tau \frac{1}{n_T} \|\Phi^T (\mathbf{K}_S \mathcal{Z} - \mathbf{K}_T) \mathbf{1}\|_2^2 \\ & + \lambda_1 \|\mathcal{Z}\|_* \end{aligned}$$

$$\text{s.t. } \Phi^T \mathbf{K} \Phi = \mathbf{I}$$

1. 基于MC的LGDM损失
2. GGDM损失
3. LRC正则化

where  $\tau$  and  $\lambda_1$  are the tradeoff parameters.

## Optimization

$$\begin{aligned}
 \min_{\Phi, \mathcal{Z}} \quad & \frac{1}{(n_T)^2} Tr(\Phi^T \mathbf{K}_S \mathcal{Z} \mathbf{D} (\Phi^T \mathbf{K}_S \mathcal{Z})^T) \\
 & + \frac{1}{(n_T)^2} Tr(\Phi^T \mathbf{K}_T \mathbf{D} (\Phi^T \mathbf{K}_T)^T) \\
 & - \frac{2}{(n_T)^2} Tr(\Phi^T \mathbf{K}_S \mathcal{Z} \mathbf{W} (\Phi^T \mathbf{K}_T)^T) \\
 & + \tau \frac{1}{n_T} \|\Phi^T (\mathbf{K}_S \mathcal{Z} - \mathbf{K}_T) \mathbf{1}\|_2^2 \\
 & + \lambda_1 \|\mathcal{Z}\|_*
 \end{aligned}$$

s.t.  $\Phi^T \mathbf{K} \Phi = \mathbf{I}$

$$\begin{aligned}
 \min_{\Phi, \mathcal{Z}, \mathcal{J}} \quad & \frac{1}{(n_T)^2} (Tr(\Phi^T \mathbf{K}_S \mathcal{Z} \mathbf{D} (\Phi^T \mathbf{K}_S \mathcal{Z})^T) \\
 & + Tr(\Phi^T \mathbf{K}_T \mathbf{D} (\Phi^T \mathbf{K}_T)^T) - 2 Tr(\Phi^T \mathbf{K}_S \mathcal{Z} \mathbf{W} (\Phi^T \mathbf{K}_T)^T)) \\
 & + \frac{\tau}{(n_T)^2} \Phi^T (\mathbf{K}_S \mathcal{Z} \mathbf{1} (\mathbf{K}_S \mathcal{Z})^T - \mathbf{K}_S \mathcal{Z} \mathbf{1} (\mathbf{K}_T)^T) \\
 & - \mathbf{K}_T \mathbf{1} Z^T (\mathbf{K}_S)^T + \mathbf{K}_T \mathbf{1} (\mathbf{K}_T)^T) \Phi + \lambda_1 \|J\|_* \\
 & + Tr(\mathcal{R}_1^T (\mathcal{Z} - \mathcal{J})) + \frac{\mu}{2} (\|\mathcal{Z} - \mathcal{J}\|_F^2)
 \end{aligned}$$

where  $\mathbf{1}$  represents a full one matrix

## Optimization

### Algorithm 1 Proposed MCTL

**Input:**  $\mathcal{X}_S \in \mathcal{R}^{m \times n_S}$ ,  $\mathcal{X}_T \in \mathcal{R}^{m \times n_T}$ ,  $\tau$ ,  $\lambda_1$

**Procedure:**

1. Compute  $\mathcal{K}_T = \varphi(\mathcal{X})^T \varphi(\mathcal{X}_T)$ ,  $\mathcal{K}_S = \varphi(\mathcal{X})^T \varphi(\mathcal{X}_S)$ ,  
 $\mathcal{K} = \varphi(\mathcal{X})^T \varphi(\mathcal{X})$ ,  $\mathcal{X} = [\mathcal{X}_S, \mathcal{X}_T]$
  2. Initialize:  $\mathcal{J}=\mathcal{Z}=\mathbf{0}$
  3. **While** not converge **do**
    - 3.1 **Step1:** Fix  $\mathcal{J}$  and  $\mathcal{Z}$ , and update  $\Phi$  by solving eigenvalue decomposition problem (9).
    - 3.2 **Step2:** Fix  $\Phi$ , and update  $\mathcal{Z}$  using IALM:
      - 3.2.1. Fix  $\mathcal{Z}$  and update  $\mathcal{J}$  by using the singular value thresholding (SVT) [53] operator on problem (11).
      - 3.2.2. Fix  $\mathcal{J}$  and update  $\mathcal{Z}$  according to gradient descent operator, i.e. Equation (13).
    - 3.3 Update the multiplier  $\mathcal{R}_1$ :  

$$\mathcal{R}_1 = \mathcal{R}_1 + \mu(\mathcal{Z} - \mathcal{J})$$
    - 3.4 Update the parameter  $\mu$ :  

$$\mu = \min(\mu \times 1.01, \max_\mu)$$
    - 3.5 Check convergence
- end while**
- Output:**  $\Phi$  and  $\mathcal{Z}$ .

*Update*  $\Phi$

$$\begin{aligned} & \frac{1}{(n_T)^2} (\mathbf{K}_S \mathcal{Z} \mathbf{D} \mathcal{Z}^T (\mathbf{K}_S)^T + \mathbf{K}_T \mathbf{D} (\mathbf{K}_T)^T - \mathbf{K}_S \mathcal{Z} \mathbf{W} (\mathbf{K}_T)^T \\ & - \mathbf{K}_T \mathbf{W} \mathcal{Z}^T (\mathbf{K}_S)^T) \Phi_{K(:,i)} + \frac{\tau}{(n_T)^2} (\mathbf{K}_S \mathcal{Z} \mathbf{1} \mathcal{Z}^T (\mathbf{K}_S)^T \\ & - \mathbf{K}_S \mathcal{Z} \mathbf{1} (\mathbf{K}_T)^T - \mathbf{K}_T \mathbf{1} \mathcal{Z}^T (\mathbf{K}_S)^T + \mathbf{K}_T \mathbf{1} (\mathbf{K}_T)^T) \Phi_{K(:,i)} \\ & = -\lambda \mathbf{K} \Phi_{K(:,i)}. \end{aligned} \quad (9)$$

*Update*  $\mathcal{J}$

$$\mathcal{J}_{K+1} = \min_{\mathcal{J}_K} \lambda_1 \| \mathcal{J}_K \|_* + \frac{\mu_K}{2} \| \mathcal{J}_K - \left( \mathcal{Z}_K + \frac{\mathcal{R}_{1K}}{\mu_K} \right) \|_F^2. \quad (11)$$

*Update*  $\mathcal{Z}$

$$\mathcal{Z}_{K+1} = \mathcal{Z}_K - \alpha \bullet \nabla(\mathcal{Z}) \quad (13)$$

## SIMPLIFIED VERSION OF MCTL

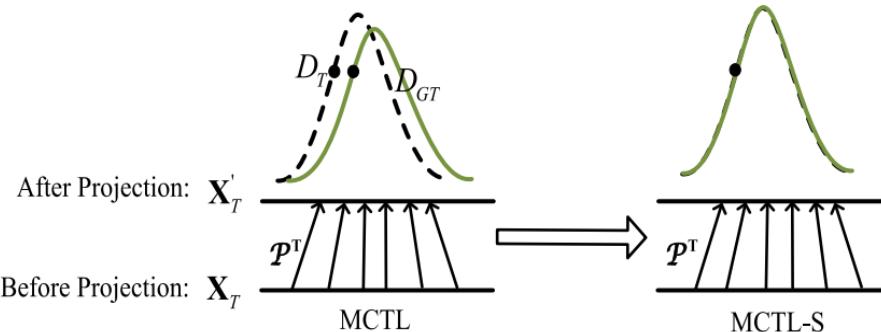


Fig. 3. Difference between MCTL (left) and MCTL-S (right). In MCTL, there is an error between the true target domain  $D_T$  and the generative target domain  $D_{GT}$ . In MCTL-S,  $D_{GT}$  is supposed to be coincided with the true target domain  $D_T$ .

$$\mathbf{X}_{GT} = \mathbf{X}_T$$

$$\mathbf{L} = \mathbf{D} - \mathbf{W}$$

$$\Phi^T \mathbf{K}_T = \Phi^T \mathbf{K}_S \mathcal{Z}$$

$$\min_{\Phi, \mathcal{Z}} \frac{2}{(n_T)^2} Tr(\Phi^T \mathbf{K}_S \mathcal{Z} \mathbf{L} (\Phi^T \mathbf{K}_S \mathcal{Z})^T) + \tau \frac{\|\frac{1}{n_T} \Phi^T (\mathbf{K}_S \mathcal{Z} - \mathbf{K}_T) \mathbf{1}\|_2^2}{\|\mathbf{1}\|_2} + \lambda_1 \|\mathcal{Z}\|_*$$

*Update*  $\Phi$

$$\begin{aligned} & \frac{2}{(n_T)^2} (\mathbf{K}_S \mathcal{Z} \mathbf{L} \mathcal{Z}^T (\mathbf{K}_S)^T) \Phi_{K(:,i)} + \frac{\tau}{(n_T)^2} (\mathbf{K}_S \mathcal{Z} \mathbf{1} \mathcal{Z}^T (\mathbf{K}_S)^T \\ & - \mathbf{K}_S \mathcal{Z} \mathbf{1} (\mathbf{K}_T)^T - \mathbf{K}_T \mathbf{1} \mathcal{Z}^T (\mathbf{K}_S)^T + \mathbf{K}_T \mathbf{1} (\mathbf{K}_T)^T) \Phi_{K(:,i)} \\ & = -\lambda \mathbf{K} \Phi_{K(:,i)} \end{aligned}$$

*Update*  $\mathcal{J}$

$$\mathcal{J}_{K+1} = \min_{\mathcal{J}_K} \lambda_1 \|\mathcal{J}_K\|_* + \frac{\mu_K}{2} \|\mathcal{J}_K - \left( \mathcal{Z}_K + \frac{\mathcal{R}_{1K}}{\mu_K} \right)\|_F^2. \quad (11)$$

*Update*  $\mathcal{Z}$

$$\mathcal{Z}_{K+1} = \mathcal{Z}_K - \alpha \bullet \bigtriangledown(\mathcal{Z}) \quad (13)$$

03

# 实验与分析



# 实验部分

## CONTENT



01 跨域图像目标识别

02 交叉姿势人脸识别

03 跨域手写数字识别

# 跨域图像目标准识别

## 4DA办公数据集



**数据集数据:**

4个域: **Caltech(C) , Amazon(A),  
DSLR(D) , Webcam(W)**

10个对象类

**实验设置:**

A中每个类选择20个样本,

另外三个域:

源域: 每个类8个样本

目标域训练: 每个类3个样本

# 跨域图像目标准识别

## 4DA办公数据集

### 实验结果：

RECOGNITION ACCURACY (%) OF DIFFERENT DA IN 4DA SETTING

4DA Tasks	Naive Comb	HFA [15]	ARC-t [9]	MMDT [33]	SGF [35]	GFK [34]	SA [60]	LTSL -PCA [40]	LTSL -LDA [40]	LSDT [41]	MCTL
$A \rightarrow D$	55.9	52.7	50.2	56.7	46.9	50.9	55.1	50.4	<b>59.1</b>	52.9	56.1
$C \rightarrow D$	55.8	51.9	50.6	56.5	50.2	55.0	56.6	49.5	<b>59.6</b>	56.0	57.3
$W \rightarrow D$	55.1	51.7	71.3	67.0	78.6	75.0	82.3	<b>82.6</b>	<b>82.6</b>	75.7	73.4
$A \rightarrow C$	32.0	31.1	37.0	36.4	37.5	39.6	38.4	41.5	39.8	42.2	<b>43.0</b>
$W \rightarrow C$	30.4	29.4	31.9	32.2	32.9	32.8	34.1	36.7	<b>38.5</b>	36.9	37.5
$D \rightarrow C$	31.7	31.0	33.5	34.1	32.9	33.9	35.8	36.2	36.7	37.6	<b>37.8</b>
$D \rightarrow A$	45.7	45.8	42.5	46.9	44.9	46.2	45.8	45.7	<b>47.4</b>	46.6	47.0
$W \rightarrow A$	45.6	45.9	43.4	47.7	43.0	46.2	44.8	41.9	47.8	46.6	<b>48.8</b>
$C \rightarrow A$	45.3	45.5	44.1	49.4	42.0	46.1	45.3	49.3	<b>50.4</b>	47.7	42.8
$C \rightarrow W$	60.3	60.5	55.9	<b>63.8</b>	54.2	57.0	60.7	50.4	59.5	57.6	59.6
$D \rightarrow W$	62.1	62.1	78.3	74.1	78.6	80.2	<b>84.8</b>	81.0	78.3	83.1	82.1
$A \rightarrow W$	62.4	61.8	55.7	<b>64.6</b>	54.2	56.9	60.3	52.3	59.5	57.2	55.7
<i>Average</i>	48.5	47.4	49.5	52.5	49.7	51.6	53.7	51.5	<b>54.9</b>	53.3	54.0

平均准确率：MCTL: 54.0%

# 跨域图像目标准识别

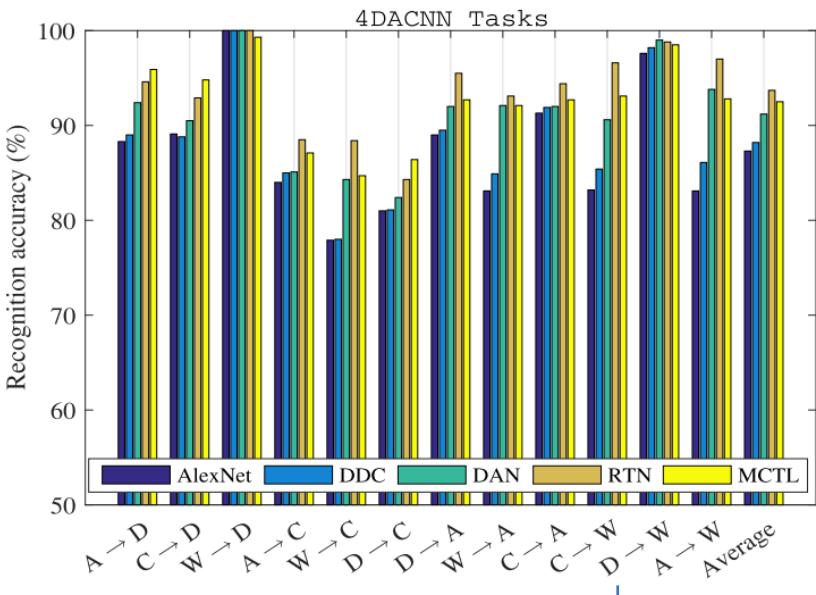
## 4DA-CNN数据集



## 实验结果：

RECOGNITION ACCURACY (%) OF DIFFERENT DA OF THE SEVENTH LAYER IN 4DACNN SETTING

4DA-CNN Tasks(f7)	SourceOnly	Naive Comb	SGF [35]	TCA	GFK [34]	LTSI [40]	LSDT [41]	MCTL
$A \rightarrow D$	81.3	94.1	92.0	82.8	94.3	94.5	<b>96.0</b>	95.9
$C \rightarrow D$	77.6	92.8	92.4	87.9	91.9	93.5	94.6	<b>94.8</b>
$W \rightarrow D$	96.2	98.9	97.6	<b>99.4</b>	98.5	98.8	99.3	99.3
$A \rightarrow C$	79.3	83.4	77.4	81.2	79.1	85.4	87.0	<b>87.1</b>
$W \rightarrow C$	68.1	81.2	76.8	75.5	76.1	82.6	84.2	<b>84.7</b>
$D \rightarrow C$	74.3	82.7	78.2	79.6	77.5	84.8	86.2	<b>86.4</b>
$D \rightarrow A$	81.8	90.9	88.0	90.4	90.1	91.9	92.5	<b>92.7</b>
$W \rightarrow A$	73.4	90.6	86.8	85.6	85.6	91.0	91.7	<b>92.1</b>
$C \rightarrow A$	86.5	90.3	89.3	92.1	88.4	90.9	92.5	<b>92.7</b>
$C \rightarrow W$	67.8	90.6	87.8	88.1	86.4	90.8	<b>93.5</b>	93.1
$D \rightarrow W$	95.1	98.0	95.7	96.9	96.5	97.8	98.3	<b>98.5</b>
$A \rightarrow W$	71.6	91.1	88.1	84.4	88.6	91.5	<b>92.9</b>	92.8
Average	79.4	90.4	87.5	87.0	87.8	91.1	92.4	<b>92.5</b>



shallow vs deep

# 跨域图像目标准识别

## COIL-20数据集



包含20个对象，1440张灰度图，每个对象72张多姿态图像，大小为128x128，灰度为256级

**实验设置：**将每张图像大小裁剪为32x32，并将数据集分为C1,C2两个子集

C1: [0°, 85°], [180°, 265°]

C2: [90°, 175°], [270°, 355°]

**C1,C2语义不同  
但相关**

RECOGNITION ACCURACY (%) OF DIFFERENT DA METHODS ON COIL-20

## 实验结果：

Tasks	SVM	TSL	RDALR [62]	DTSL [43]	LTS defense [40]	LSDT [41]	MCTL
$C1 \rightarrow C2$	82.7	80.0	80.7	84.6	75.4	81.7	<b>84.8</b>
$C2 \rightarrow C1$	84.0	75.6	78.8	<b>84.2</b>	72.2	81.5	83.7
Average	83.3	77.8	79.7	<b>84.4</b>	73.8	81.6	84.3

# 跨域图像目标准识别

## MSRC4和VOC 2007数据集：

### 不同数据集的跨域识别问题

实验结果：



构造相同的标签集



MSRC

VOC 2007

数据挖掘

RECOGNITION ACCURACY (%) OF DIFFERENT DA METHODS ON MSRC AND VOC 2007 DATA SETS

Tasks	SVM	TSL	RDALR [62]	DTSL [43]	LTS defense [40]	LSDT [41]	MCTL
$M \rightarrow V$	37.1	32.4	37.5	38.0	38.0	<b>47.4</b>	<b>47.4</b>
$V \rightarrow M$	55.5	43.2	62.3	56.4	<b>67.1</b>	63.9	64.8
Average	46.3	37.8	49.9	47.2	52.6	55.6	<b>56.1</b>

MSRC,VOC2007共有六个语义类：飞机，自行车，鸟，汽车，牛，羊。

实验设置：

取M中1269幅图像为源域，V中1530幅图像为目标域，然后切换。

# 交叉姿势人脸识别

挑战：

人脸的三维位置姿势变化是一个**非线性**的传递问题，一般的识别模型**对于姿势的变化十分敏感**，因此基于姿势变化的人脸识别问题处理具有一定的挑战性。



## CMU Multi-PIE人脸数据集



选用数据集中前60名受试者在两种不同环节下的面部图像，构建了**S1**和**S2**两个域数据，S1为中性表情下的每类还有七张不同姿势的图像，S2与S1相似，为七张微笑表情下的不同姿势的图像。

**实验设置：** S1: S : 0°正面脸 T:60°脸 ; S2与S1相同  
S1+S2: S: 0°正面脸x2 T :60°脸 x2  
S1->S2: S: S1 T:S2的0°和60°脸为训练，其余测试

# 交叉姿势人脸识别

## 实验结果：

RECOGNITION ACCURACY (%) OF DIFFERENT DA METHODS ON FACE RECOGNITION ACROSS POSES

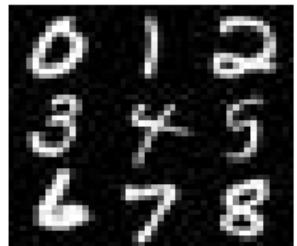
Tasks	Naive Comb	A-SVM	SGF [35]	GFK [34]	SA [60]	LTSI [40]	LSDT [41]	MCTL
$S_1 (0^\circ \rightarrow 60^\circ)$	61.0	57.0	53.7	61.0	51.3	56.0	59.7	<b>65.3</b>
$S_2 (0^\circ \rightarrow 60^\circ)$	62.7	62.7	55.0	58.7	62.7	62.7	63.3	<b>70.0</b>
$S_1 + S_2 (0^\circ \rightarrow 60^\circ)$	60.2	60.1	53.8	56.3	61.7	60.2	61.7	<b>68.3</b>
$S_1 \rightarrow S_2$	93.6	94.3	92.5	96.7	98.3	97.2	95.8	<b>98.7</b>
<i>Average</i>	69.4	68.5	63.8	67.0	68.5	70.3	70.1	<b>75.6</b>

对于非线性传递问题。这也证明了基于中间域生成的迁移学习可以更好地解释LGDM，改善非线性局部迁移问题

# 跨域手写数字识别

## 手写数字数据集

MNIST



SEMEION



USPS



MINST:7万张28x28图像

SEMEION:9298张16x16图像

USPS: 2593张16x16图像

**实验设置：**将M中的图像裁剪为16x16，分别将三个数据集中的一  
个作为源域，其他作为目标域，一共有6个跨域任务。源域中每类  
随机抽100个样本，目标域随机抽10个样本并使用五个随机分割。

# 跨域手写数字识别

## 手写数字数据集

### 实验结果：

RECOGNITION ACCURACY (%) OF DIFFERENT DA ON HANDWRITTEN DIGITS RECOGNITION

Tasks	Naive Comb	A-SVM	SGF [35]	GFK [34]	SA [60]	LTSI [40]	LSDT [41]	MCTL
$M \rightarrow U$	78.8	78.3	79.2	82.6	78.8	83.2	79.3	<b>87.8</b>
$S \rightarrow U$	83.6	76.8	77.5	82.7	82.5	83.6	84.7	<b>84.8</b>
$M \rightarrow S$	51.9	70.5	51.6	70.5	<b>74.4</b>	72.8	69.1	74.0
$U \rightarrow S$	65.3	74.5	70.9	76.7	74.6	65.3	67.4	<b>83.0</b>
$U \rightarrow M$	71.7	73.2	71.1	74.9	72.9	71.7	70.5	<b>81.2</b>
$S \rightarrow M$	67.6	69.3	66.9	74.5	72.9	67.6	70.0	<b>74.0</b>
<i>Average</i>	69.8	73.8	69.5	77.0	76.0	74.0	73.5	<b>80.8</b>

其中：MCTL表现出了最好的性能平均准确率达到了80.8%，比之其他最好性能的方法也高3%

# 实验结果

## 总结

所有任务对比：

AVERAGE PERFORMANCE OF ALL TRANSFER TASKS

All Transfer Tasks	LTS defense [40]	LS Defense [41]	MCTL
Average (%)	69.45	71.08	73.88

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多数任务：较好性能  
部分任务：微小改进  
**所有任务综合：具有较大优势，比**  
起性能最佳的LTS defense和LS Defense也具有更  
好性能  
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# 分析与讨论

CONTENT



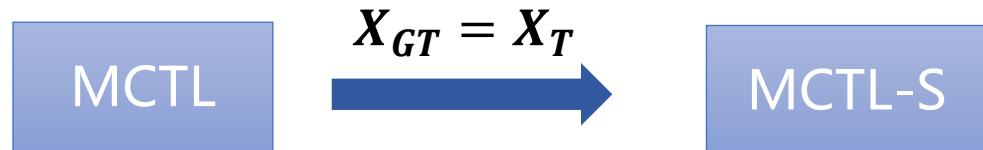
01 MCTL-S

02 参数设置与消融分析

03 模型维度和参数分析

04 计算复杂度与时间分析

05 模型可视化与收敛



## 实验结果对比：

RECOGNITION ACCURACY (%) IN 4D CNN DATA SET

4DA-CNN Tasks	MCTL	MCTL-S
$A \rightarrow D$	95.67	95.71
$C \rightarrow D$	94.69	94.72
$W \rightarrow D$	99.25	99.29
$A \rightarrow C$	87.11	87.05
$W \rightarrow C$	84.73	84.74
$D \rightarrow C$	86.37	86.34
$D \rightarrow A$	92.66	92.65
$W \rightarrow A$	92.06	92.07
$C \rightarrow A$	92.68	92.06
$C \rightarrow W$	93.08	93.04
$D \rightarrow W$	98.49	98.51
$A \rightarrow W$	92.79	92.83
Average	92.47	92.47

RECOGNITION ACCURACY (%) IN COIL-20

COIL-20	MCTL	MCTL-S
$C1 \rightarrow C2$	84.83	85.00
$C2 \rightarrow C1$	83.67	83.67
Average	84.25	84.34

MCTL与MCTL-S具有相似性能

## 模型参数：

权衡系数 $\tau$ 和 $\lambda_1$ 固定为1

公共子空间维数: $d=n$

使用高斯核函数

$$k(x_i, x_j) = \exp(-\|x_i - x_j\|^2/2\sigma^2)$$

## 消融分析

解释MCTL模型中的GGDM,LGDM,LRC三个项目每一项的影响。

## 实验设置

在COIL-20对象识别任务，手写数字识别任务和MSRC-VOC2007跨域图像识别任务上进行消融分析实验。

RESULTS OF ABLATION ANALYSIS

Tasks	MCTL	no LGDM	no LRC	no GGDM
$C1 \rightarrow C2$	<b>77.0</b>	73.0	76.7	76.8
$M \rightarrow U$	71.0	70.0	67.0	<b>73.0</b>
$V \rightarrow M$	70.2	70.1	70.1	<b>70.3</b>
Average	72.7	71.0	71.2	<b>73.4</b>

**LGDM重要性更高**

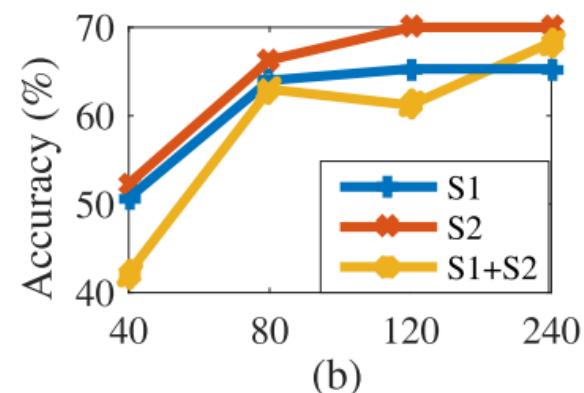
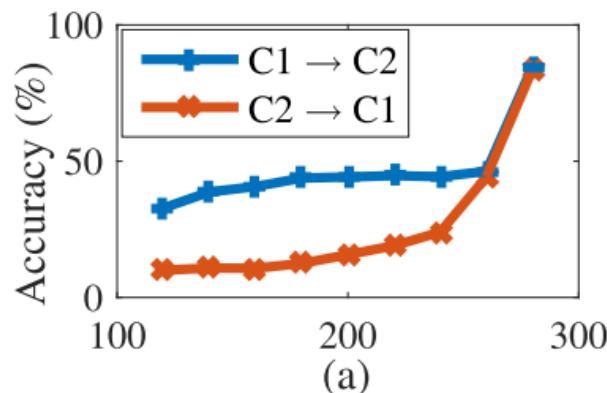
# 模型维度与参数分析

## 维度分析：

MCTL模型学习了一个**公共子空间P**

研究在COIL-20和CMU Multi-PIE人脸数据

集中MCTL在**不同子空间维数下的性能变化**

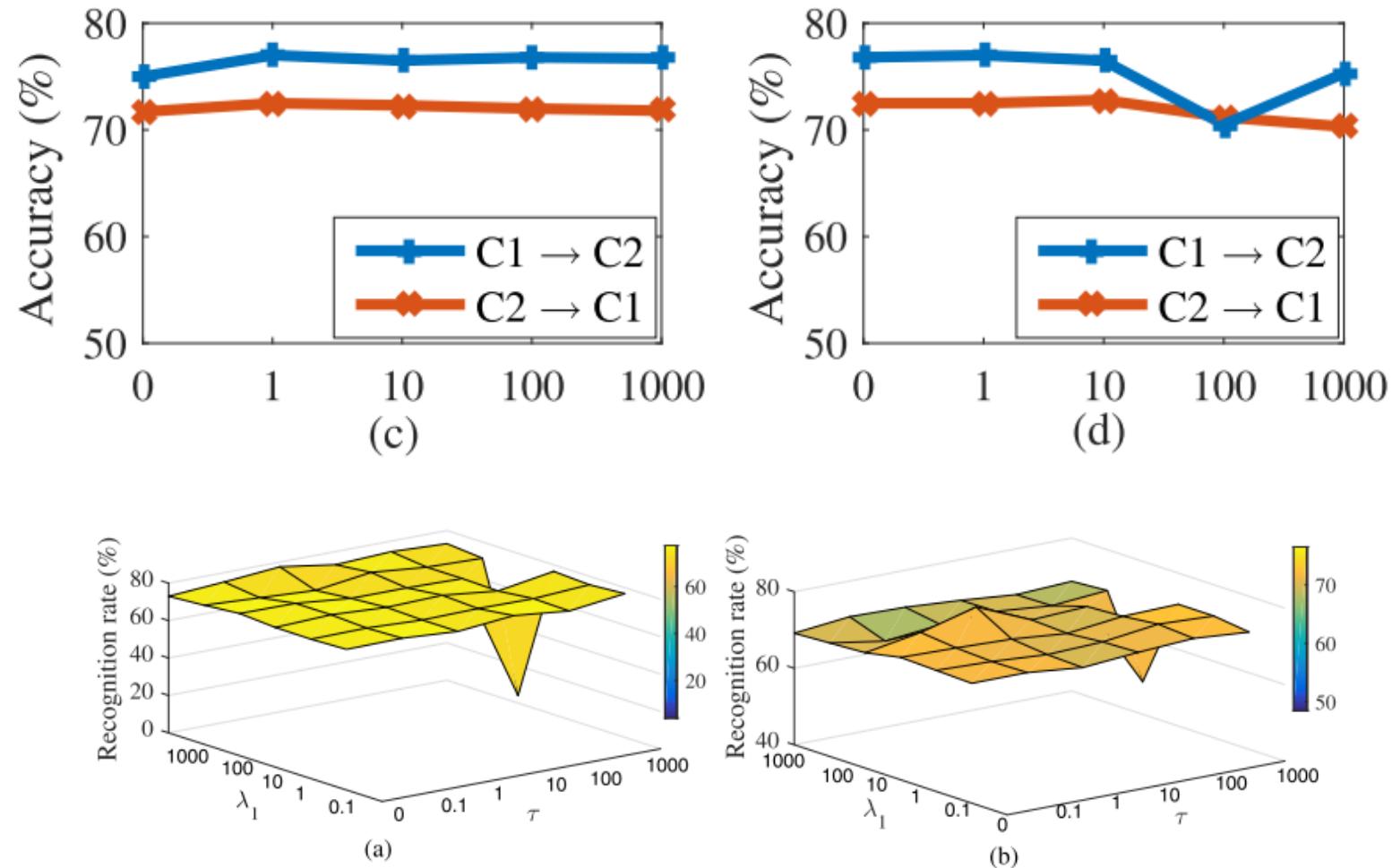


一般情况下，维数增加，性能提高

# 模型维度与参数分析

## 参数灵敏度：

MCTL模型中参数调整主要涉及两个权衡参数 $\tau$ 和 $\lambda_1$ ，这里研究他们对模型的敏感性，两个参数均按照{0, 1, 10, 100, 1000}进行调整参数，得到结果如图所示，并且进行一个参数调整时将另一个参数固定为1。



$\tau$ 和 $\lambda_1$ 共同调整，

# 计算复杂度和时间分析

计算复杂度：

算法1：update J, update Z, update  $\omega$

计算中涉及的特征分解和矩阵乘法的复杂度为 $O(n^3)$

update J, update Z的复杂度为 $O(n^2)$

设迭代次数为T，则总计算复杂度= $O(tn^3) + O(tn^2)$

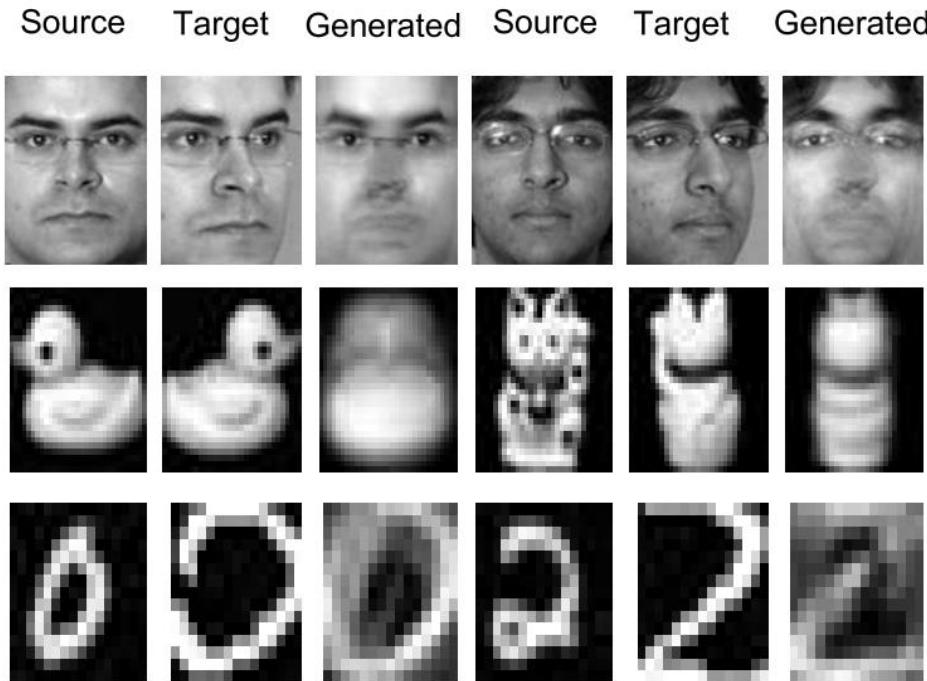
COMPUTATIONAL TIME ANALYSIS AND RECOGNITION ACCURACY (%)

Tasks	SGF [35]	GFK [34]	SA [60]	LTSI [40]	MCTL
$S1 \rightarrow S2$	10.9s (92.5%)	1.5s (96.7%)	4.18s (98.3%)	7.21s (97.2%)	7.62s (97.3%)
$M \rightarrow U$	75s (79.2%)	12.2s (82.6%)	30.5s (78.8%)	62.1s (83.2%)	98.8s (87.8%)

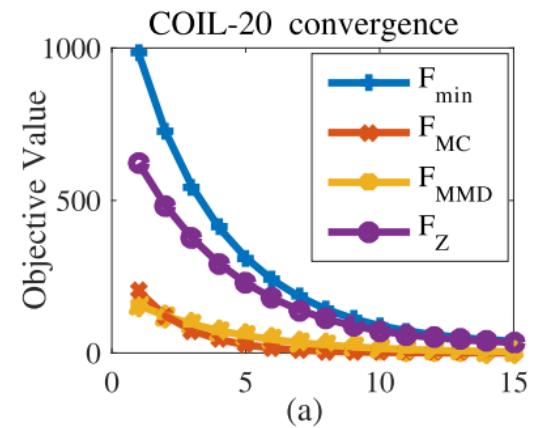
计算时间

# 模型可视化与收敛

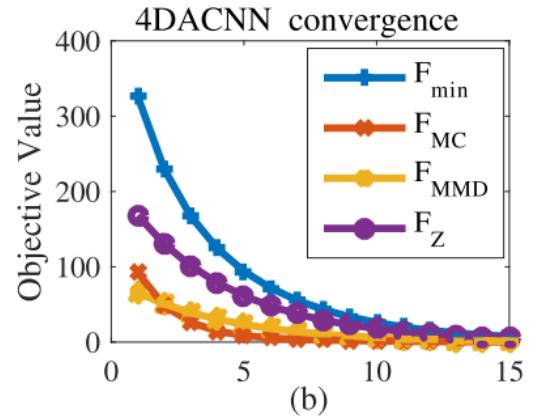
## 特征可视化



## 收敛性



迭代次数：15



# Thanks