四川邮电职业技术学院

Sichuan Post and Telecommunication College

论文集

二〇一二年

目 录

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聚类分析企业的技术密集水平

陈蕾蕾

摘要:本文应用模糊聚类法分析某市汽车产业的企业技术密集水平,使有限的资源得到更有效地配置和利用,促进产业内各的优化和进步,提高企业竞争力

关键词:模糊相似矩阵 绝对值指数法 模糊聚类分析

中图分类号:G640 文献标识码:A DOI:10.3969/j.issn.1672-8181.2011.04.146

1 引言

在今天这个经济高度发展的社会,企业的技术密集水平成为衡量一个企业实力的标准之一。不同的企业具有不同的技术密集水平,如何对他们进行归类分析呢?

2 问题的提出

某市的汽车生产产业有8家企业,这些企业的技术密集水平如何呢?其差别在哪里呢?

为了解决以上问题,我们采用以下3个指标来衡量企业的技术密集水平:生产工人劳动生产率、每百万元固定资产所容纳的职工人数、技术管理人员在职工中的比重。通过调研统计这8家企业,我们得出如下数据:

	企业1	企业2	企业3	企业4	企业5	企业6	企业7	企业8
生产工人劳动生产率	1.8	2.1	3.2	2.2	2.5	2.8	1.9	2.0
职工人数/每百万元	95	99	101	103	98	102	120	130
技术管理人员比重	0.15	0.21	0.18	0.17	0.16	0.20	0.09	0.11

其中第一个指标的单位是万元/(年.人)。

3 问题的分析

俗话说得好,"物以类聚",把事物进行分类处理,可以有效地帮助我们比较事物的异同,分析各类事物的特征,提高认知和管理事物的能力。那么,就这个问题,我们采用模糊聚类的方法来说明这8家企业技术密集水平的差异。

这8家企业我们可以看做是一个论域U,每个企业用表示u_i(i=1,2…8),则记U={u_1,u_2…u_8},令各企业的上述3个指标为,即:

u_1=(1.8,95,0.15) u_2=(2.1,99,0.21) u_3=(3.2,101,0.18)

u_4=(2.2,103,0.17) u_5=(2.5,98,0.16) u_6=(2.8,102,0.20)

u_7=(1.9,120,0.09) u_8=(2.0,130,0.11)

由上述数据,我们按照模糊聚类的方法对这8家企业进行聚类分析。

4 模糊聚类分析

第一步:建立原始数据矩阵

因为在第一个指标中的单位是万元/(年.人),而第二个指标是每百万元固定资产所容纳的职工人数,其单位是人/百万,第三个指标没有单位。为了消除量纲的影响,需要将数据做适当的变换,这里可以采取将第二个指标同时除以100以缩小变量间的数量级的方法,由此得到数据矩阵:

$$\begin{pmatrix} 1.8 & 0.95 & 0.15 \\ 2.1 & 0.99 & 0.21 \\ 3.2 & 1.01 & 0.18 \\ 2.2 & 1.03 & 0.17 \\ 2.5 & 0.98 & 0.16 \\ 2.8 & 1.02 & 0.20 \\ 1.9 & 1.20 & 0.09 \\ 2.0 & 1.30 & 0.11 \end{pmatrix}$$

第二步:标定——建立模糊相似矩阵

由于上面的矩阵中所给数据x_{ij}>0,所以直接采用绝对值指数法建立模糊相似矩阵R,

第i个样本与第j个样本的相似系数为: $r_{ij}=e^{-\sum_{k=1}^{s}|x_{ik}-x_{jk}|}$

利用相应软件可以得到如下相似矩阵R为(保留四位有效数字):

$$R=\begin{pmatrix} 1 & 0.670 & 0.225 & 0.607 & 0.477 & 0.326 & 0.663 & 0.554 \\ 0.670 & 1 & 0.317 & 0.835 & 0.631 & 0.477 & 0.589 & 0.601 \\ 0.225 & 0.317 & 1 & 0.357 & 0.472 & 0.651 & 0.206 & 0.210 \\ 0.607 & 0.835 & 0.357 & 1 & 0.698 & 0.527 & 0.577 & 0.589 \\ 0.477 & 0.631 & 0.472 & 0.698 & 1 & 0.684 & 0.411 & 0.419 \\ 0.326 & 0.477 & 0.651 & 0.527 & 0.684 & 1 & 0.304 & 0.310 \\ 0.663 & 0.589 & 0.206 & 0.577 & 0.411 & 0.304 & 1 & 0.803 \\ 0.554 & 0.601 & 0.210 & 0.589 & 0.419 & 0.310 & 0.803 & 1 \end{pmatrix}$$

第三步:用二次方法求相似矩阵R的传递闭包t(R)

经过检验,上面的模糊相似矩阵R还不具有传递性,即R还模糊等价矩阵。为了进行分类,还需要将R改造成模糊等价矩
因此,我们用二次方法求模糊相似矩阵R的传递闭包t(R):

故最后得=t(R)=R*==
$$\begin{pmatrix} 1 & 0.670 & 0.225 & 0.607 & 0.477 & 0.326 & 0.663 & \cdots \\ 0.670 & 1 & 0.317 & 0.835 & 0.631 & 0.477 & 0.589 & \cdots \\ 0.225 & 0.317 & 1 & 0.357 & 0.472 & 0.651 & 0.206 & \cdots \\ 0.607 & 0.835 & 0.357 & 1 & 0.698 & 0.527 & 0.577 & \cdots \\ 0.477 & 0.631 & 0.472 & 0.698 & 1 & 0.684 & 0.411 & \cdots \\ 0.326 & 0.477 & 0.651 & 0.527 & 0.684 & 1 & 0.304 & \cdots \\ 0.663 & 0.589 & 0.206 & 0.577 & 0.411 & 0.304 & 1 & \cdots \\ 0.554 & 0.601 & 0.210 & 0.589 & 0.419 & 0.310 & 0.803 & \end{pmatrix}$$

第四步:将λ由大到小进行聚类

λ=1,将U分为8类:{u_1},{u_2},{u_3},{u_4},{u_5},{u_6},{u_7},{u_8}

λ=0.835,将论域U分为7类:{u_1},{u_2,u_4},{u_3},{u_5},{u_6},{u_7},{u_8}

λ=0.803,将论域U分为6类:{u_1},{u_2,u_4},{u_3},{u_5},{u_6},{u_7,u_8}

λ=0.698,将论域U分为5类:{u_1},{u_2,u_4,u_5},{u_3},{u_6},{u_7,u_8}

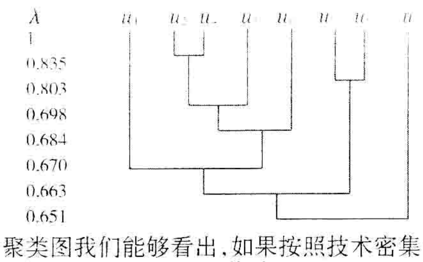
λ=0.684,将论域U分为4类:{u_1},{u_2,u_4,u_5,u_6},{u_3},{u_7,u_8}

λ=0.670,将论域U分为3类:{u_1,u_2,u_4,u_5,u_6},{u_3},{u_7,u_8}

λ=0.663,将论域U分为2类:{u_1,u_2,u_4,u_5,u_6,u_7,u_8},{u_3}

λ=0.651,将论域U分为1类:{u_1,u_2,u_3,u_4,u_5,u_6,u_7,u_8}

第五步:由上述结果得动态聚类图如下:



由聚类图我们能够看出,如果按照技术密集水平从高到低这8家企业排序的话,那么依次是{u_2},{u_4},{u_7},{u_8},{u_5},
{u_1},{u_3}。

5 结语

综上所述,用模糊聚类分析的方法得到不同企业的技术密集水平,可以有目的地帮助技术密集程度低的企业向技术密集程度高的企业学习,有利于发挥科技人才的作用,提高企业的生产率,促进新技术的开发和利用,同时,可以使有限的资源向更具生存力和竞争力的企业流动,发挥资源效力,从而促使整个产业得到发展壮大。

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作者简介:陈蕾蕾(1980—),女,汉族,讲师,硕士,现任教于四川职业技术学院基础部,一直从事《高等数学》、《经济数学》、《概率统计》等科目地教学工作,研究方向为应用数学,四川成都 610067

文章编号: 1003- 7136(2011) 03- 0088- 03

高职院校图书馆资源利用探析

陈　燕,李　娟

(四川邮电职业技术学院 图书馆,四川 成都　610067)

摘　要:高职院校图书馆在硬件方面发生了很大的变化,但其资源利用率却普遍偏低,文章从造成其资源利用率低的原因出发,提出有效利用高职院校图书馆资源的建议。

关键词:图书馆;利用率;高职院校

中图分类号:G252 5　　文献标识码:A

随着高等教育的大众化、国际化和教育需求的多样化,我国高等职业教育也得到了迅猛的发展,高职院校图书馆也随着发生了巨大的变化。从四川省的高职院校图书馆来看(表 1、2),大量的图书馆从以前的无独立馆舍、购书经费紧缺、电子资源种类单一、传统手工管理变成了环境优雅、资金充裕、电子资源丰富的现代化图书馆。但与本科院校所不同,高职院校资源的飞速增长与读者的利用情况却并未成正比,如何把高职院校学生吸引到图书馆,充分利用好图书馆的资源,成为目前亟待解决的问题。

表 1　2005年四川省高职院校图书馆基本情况

	馆舍 5000m²	馆舍 10000m²	购书经费 20万/年	购书经费 100万/年	开设 文献检索课	电子资源	自建资源库
数量	4	0	3	0	3	13	0

表 2　2010年四川省高职院校图书馆基本情况

	馆舍 5000m²	馆舍 10000m²	购书经费 20万/年	购书经费 100万/年	开设 文献检索课	电子资源	自建资源库
数量	15	11	12	10	12	28	6

1　造成高职院校图书馆资源利用率低的原因

1.1　学生重视动手能力,忽略理论知识

高等职业技术教育主要培养面向生产、管理、服务第一线需要的,既有大学层次的专业知识,又有较强实践能力的,具有高素质和实用性技能的高级技术人才和管理人才,高职教育的培养目标决定了它的专业设置、课程建构、教学方法的特殊性,在要求学生掌握必要的理论知识的同时,还注重培养学生的实践能力及生产、建设、管理和服务中某一方面的专业技能。因此,在课程设置和培养理念方面都及其重视学生的实验动手能力,大量的课程都集中在实验实训中。高职学生总学制为三年,第三年几乎所有的学生都出去实习了,再加上高职类学生在理论知识方面基础偏低,所以即使图书馆资源大量增加,环境改善,但大量的学生仍然没有到馆借阅的习惯,有的几乎到毕业时才第一次到图书馆。在平时的借阅中,也表现出文学类书籍借阅集中,而专业书籍借阅偏少,阅读范围狭窄的情况,甚至大量学生把图书馆当作休闲的场所,忽视图书馆作为信息传递中心的作用。这就造成大量图书资源的浪费,降低了图书资源的利用率。

1.2　对馆藏资源不熟悉

从 2005年到 2010年期间,四川省 80% 以上高职院校图书馆实现了从传统闭架式管理向自动化管理过渡,读者入馆、查询、借阅以及资源分布都发生了很大的变化。很多读者观念和习惯还没转变过来,在他们看来,刷卡通过门禁系统进入图书馆是第一道障碍,用查询系统查找自己所需图书,由于不熟悉,显得有困难,同时由于大量的读者在开架式阅览室取书时,乱插乱放图书,让一些读者在找书过程中,未能及时准确地找到自己所需图书,因此其阅读积极性就大打折扣。

1.3　文献检索知识欠缺,电子资源不会用或很少使用

收稿日期: 2011- 03- 05

随着图书管理方式的转变以及数字图书馆技术的发展，四川省内所有的高职院校都购买有维普或超星等电子资源，海量的数字化信息对读者的检索知识有了更高的要求，但大多数高职院校并未开设文献检索相关课程，甚至新生电子资源使用培训都很少，因此，这又为读者使用图书查询系统或者电子资源设置了极大的障碍，一方面不知道有哪些资源可用，另一方面不知道如何检索资源。如某校《中文科技期刊数据库》半年的下载数量（表 3），按照学校 5000人计算，一学期人均访问率仅有 3.5次，可见平时电子资源访问次数确实偏少。文献检索知识欠缺也是造成高职院校图书馆的电子资源利用率低的重要原因。

表 3 2010年上学期某高职院校《中文期刊数据库》访问统计

时间	一月	二月	三月	四月	五月	六月
访问人数	1359	1078	1501	1487	1681	1706
下载篇数	4125	3694	4441	4159	4979	5082

1.4 馆藏结构不合理

由于高职院校大多是由以前的中专升成的大专，因此高职院校图书馆的图书大多比较陈旧，有的甚至连续几年没有购书，随着升大专的需求，很多图书馆采取了突击购书的方式，这就导致很多图书馆采购了相当大一批质量差、陈旧或者大量的价格便宜的文学书，这不仅造成藏书比例失调，专业书籍不足，更使广大读者在关键时候需要图书时找不到适合自己的书，从而大大降低了读者的积极性。同时，由于藏书中存在大量的长期未进行剔除的老书或破损书籍，藏书时效性差，再加之馆内未设立专门的新书展区或常流通书专区，新老书夹杂在一起，各书库藏书标示不清晰，使得读者在书架上找书时盲目、费时，这也在很大程度上降低了高职院校图书馆的资源利用率。

1.5 流通部工作人员长期形成的职业倦怠

目前，部分高职院校图书馆流通部的工作人员专业知识欠缺，服务意识不强，工作效率相对低，因此很少积极主动思考如何更好地服务读者，而更多的精力花在了如何保护好藏书上，如为避免大部头的工具书被损坏，将大量的书籍锁起来用于“观赏”，造成大量珍贵的书籍变成“死书”，这些都极大地阻碍了图书资源的利用。同时，由于流通部人员长期形成的理念以及专业技术水平偏低，面对读者的相关咨询，很难给出读者满意的答案，形成读者利用图书馆信息的“鸿沟”，以至于大量的新书、好书闲置，造成各种资源的浪费。

1.6 高职院校学术氛围不够浓厚

图书馆作为大学的文献信息中心，在教学和科研方面都发挥着非常重要的作用，但基于高职院校重在培养动手能力强的技术性人才，因而学生也热衷于上实验课程，忽视理论学习。长期的学习习惯导致大量学生对理论学习和学术知识完全提不起兴趣，甚至在做毕业设计的时候都不会想到从图书馆查询参考资料作为论文的重要素材，而是草草地写完论文，完成任务了事；全然不知道图书馆的电子资源有哪些，更不用说可以试用电子资源做论文的参考资料，这些都是造成图书馆资源利用率低、资源浪费的重要原因。

2 关于提高高职院校图书馆资源利用率的建议

2.1 转变高职院校学生观念，加大资源宣传力度

根据目前市场对人才需求的情况看，仅仅拥有一项职业技术已经远远不能满足企业的需求了，企业需要的是掌握技能，同时综合素质都比较强的人才。因此，高职院校也需要培养有素养、有品位的大学生，而图书馆则是学生吸取营养、厚积薄发的一个基地。图书馆可通过向学生推荐新书、好书以及张贴常到馆人员排行予以表彰等方式吸引读者，同时加强对图书馆所拥有的纸质藏书以及电子资源进行宣传，让读者了解图书馆目前所有的可利用资源。

2.2 开展多样化培训，营造良好学术氛围

由于新生刚到学校，对图书馆的各种资源都不太了解，甚至少数学生不知道图书馆在什么位置，因此开展“如何利用图书馆”的培训是很有必要的，这可以让大多数学生了解图书馆的馆藏资源结构、如何使用查询系统，准确地找到自己想要的书，在学生利用图书馆资源的过程中，形成良好的学术氛围。同时由于大多数高职图书馆都购买了昂贵的电子资源，而学生却不了解有哪些电子资源，不知道如何使用，所以图书馆可组织如何利用电子资源的培训。鉴于大多数高职院校教职人员紧缺，图书馆专业人员稀缺，图书馆可请数据库商派专业的培训人员到学校组织相关培训，既节约了人力物力财力，又达到提高学生信息检索能力的目的。

2.3 把握读者特点并掌握图书流通规律

高职院校区别于其他高等院校在于它有很浓厚的行业色彩，如电力、通信、交通等等，因此在购书方面必须把握好读者所在行业的特点，有针对性地购买适合业内读者的好书，尤其是在专业书籍方面，既要选择行业内的好书，又要适合高职院校这个层次学生的读物，如购买职业鉴定类的书籍、计算机和英语考级类书籍、专科升本科等这些学生常用的书籍。在复本上可考虑比普通的图书多两三本，尽量缩短读者借阅周期；同时从借阅的情况来看，文学休闲类书籍借阅率相对高，这些也是备受学生青睐的书籍，因此，这类书籍可在保持结构合理的情况下做到常更新，并及时购买一些畅销

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书籍，吸引读者，让更多的读者能到馆借书。

2.4 设置合理的馆藏结构，使文献资源合理化配置

待图书馆新书补充到一定程度，定期进行剔旧工作，这样大量的新书有更多摆放的位置，也让读者一眼能看到富有生机的新书和好书，方便查阅。对于目前高职院校图书馆才转变不久的开架式管理，很多读者不太适应，如果馆藏结构分布不合理，容易造成读者资源无处寻的局面，因此，考虑到高职院校图书馆读者的特殊需求，可设立不同的专区：如新书展区、(行业)特色资源展区、职业鉴定和职业技术书籍专区、英语和计算机书籍专区以及常流通书专区，这些常用的书籍可展放在离"借还书处"比较近的地方，一方面位置醒目，另一方面也免于读者抱着书在馆内转圈，工作人员上书也比较容易。

2.5 加强馆员培训，提高综合素质

图书馆员是图书馆的灵魂，因此图书馆员的素质对读者有巨大的影响。数字图书馆技术不断的发展，对图书馆员提出了新的要求，不仅要求馆员要懂图书馆学的检索等知识，还要懂英语、计算机、网络技术等等；同时图书馆发展到现在出现了许多咨询方面的问题，对图书馆员的职业素养以及服务态度也有了更高的要求，需要的更是综合性人才，因此应加强对馆员的培训，这样才能提高馆员的综合素质，更好地服务读者。

3 结语

图书馆是高等职业教育办学的基本组成部分，也是学校的知识宝库和文献信息中心。在高职院校创建省级乃至国家级示范性高职院校、培养高技能应用型创新人才和满足市场需要的过程中，图书馆丰富、高品位的藏书资源，显示着它的教育实力和地位，是素质与创新教育的重要保障。充分发挥图书馆的职能作用，将有力地促进高职院校的创新教育。随着图书馆的日益发展以及由此而带来的一系列机遇和挑战，高职院校图书馆要根据其自身特点，制定适合于自己发展、吸引读者、促进读者有效利用图书馆资源的措施，从而创新性地做好高职院校图书馆的服务工作。通过多渠道、创新性的举措，才能有利于图书馆的长远发展和图书人力资源的可持续发展，完成图书馆的"知识传递"这一创造性劳动。

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Analysis of Resources Utilization Ratio in Higher Vocational College Libraries

CHEN Yan, LI Juan

(Sichuan Post and Telecommunication Vocational College, Chengdu 610067, China)

Abstract Great changes have taken place about hardware in higher vocational college libraries, but the resources utilization ratio is common low. Based on the analysis of the reason of low resources utilization ratio, some suggestions for making full use of the resources in higher vocational college libraries are proposed in this article.

Key words library, utilization ratio, higher vocational college

作者简介：

陈燕，女，管理学学士，四川邮电职业技术学院图书馆助理馆员。

李娟，女，四川邮电职业技术学院图书馆馆员。

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Radar HRRP Recognition Based on Discriminant Information Analysis

JIANSHENG FU[1] XIAOHONG DENG[2] WANLIN YANG[1]
[1]College of Electronic Engineering, University of Electronic Science and Technology of China
No.4, Section 2, North Jianshe Road, Chengdu
CHINA
[2]Sichuan Post and Telecommunication College
No.536, Jingkang Road, Chengdu
CHINA
fujiansheng2010@126.com 50561736@qq.com wlyang@uestc.edu.cn

Abstract: In radar HRRP target recognition, the quality and quantity of Discriminant Information (DI), which one is more important? Accompanied with this issue, the paper proceeds to delve into DI analysis, and accordingly, three fundamental DI extraction models are proposed, i.e., PGA, PIB and AIB. Among these models, PIB and AIB both aim to obtain Between-class DI (B-DI) from individual standpoints while PGA obtains Among-class DI (A-DI) from a general viewpoint; PGA and PIB are both used for passive recognition while AIB for active recognition. In order to externalize these models, we conduct Generalized Discriminant Analysis (GDA) into them, and two GDA variations come forth, i.e., PIB-based GDA (PIB-GDA) and AIB-based GDA (AIB-GDA). Theoretical analyses and experimental results indicate as follows. Firstly, although PGA prevails in pattern recognition, but the implementation prospect is hardly optimistic on account of the weak anti-fading ability of A-DI. Compared with PGA, PIB and AIB are both more suitable to multi-class discrimination due to the relative stability of B-DI. Secondly, in general, PIB-GDA is inferior to AIB-GDA but superior to GDA to many challenges, such as computational efficiency, target quantity, aspect and sample variation, noise disturbance, etc.

Key-Words: discriminant information, feature extraction, target recognition, generalized discriminant analysis.

1 Introduction

Mathematical speaking, mutual information (MI) represents the reduction of uncertainty in one random variable when the value of another related random variable is known, so it can expose a dependency between two random variables even when that dependency is nonlinear [1]. As a fundamental concept of information theory, MI always appears in pattern recognition for feature extraction [2]–[4], whereas it is impractical to calculate MI in high dimensions due to the unfeasible number of samples and long operating time [5], [6]. In order to avoid this complex time-consuming process, a simple concept, namely, Discriminant Information (DI), is proposed for radar HRRP target recognition, here DI is defined as the information which can denote part of its class' characters and can be used to discriminate its class from others. The essence of DI analysis is to select and utilize special DI components via applying a certain Feature Extraction Method (FEM), thereby obtaining the related Feature Templates (FTs) which contain the appointed DI components. Not only can different DI utilizations result in different classifycation performances, but also a proper DI analysis is very conducive to feature extraction. Nevertheless we are usually subject to many statistical FEMs but neglect the DI components they aim for, and as a result, the thought of DI analysis is seldom accorded due respect from HRRP-based Radar Automatic Target Recognition (RATR) communities.

A raw HRRP is the amplitude of the coherent summations of the complex time returns from target scatters in each range resolution cell, which represents the projection of the complex returned echoes from the target scattering centers onto the radar Line Of Sight (LOS). Among several kinds of wideband radar target signatures, HRRP is a promising signature and easier to be acquired, but highly sensitive to time-shift and target-aspect variation, so how to extract robust and effective feature from it becomes a key problem in HRRP-based RATR. During past years, many RATR communities confirmed that raw HRRP contains some target structure signatures, such as scatter distribution, size, etc [7]–[10], and accordingly, a number of pretreatment methods, such as discrete Fourier transform [11], wavelet transform [12], etc, have been adopted to extract its time-shift invariants, such as amplitude, spectra, etc [3], [4], [8], [9], [13]–[17], as the feature dataset for the discriminant analysis and recognition.

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In this paper, we mainly concern with discriminant analysis. Generally speaking, the chief aim of discriminant analysis is to obtain the FTs which contain DI as much as possible, and synchronously, to adjust the recognition speed as per the practical demand. There are multifarious FEMs for discriminant analysis [3], [4], [8], [9], [13]–[33]. As the traditional decomposition methods, Principal Component Analysis (PCA) and Kernel PCA (KPCA) always appear in pattern recognition [18]–[21], but both obtain feature information from an energy viewpoint instead of DI, so they overlook the redundancy information in principal components. As the classical discriminant methods, Linear Discriminant Analysis (LDA) and kernel Generalized Discriminant Analysis (GDA) have been widely applied for feature extraction and dimensionality reduction [22]–[26], but both are prevalently designed to obtain Among-class DI (A-DI) at the expense of Between-class DI (B-DI), thereby losing the relative DI components between two random targets and resulting in a dissatisfied classification performance sometimes.

Therefore, DI continually decreases along the whole feature extraction process. In raw data preprocess, we can obtain the time-shift invariant DI but abandon the useful DI in variant components. In discriminant analysis process, we prefer to A-DI while A-DI is only one subset of DI. Furthermore, different DI components always have different stabilities of information content, and different FEMs usually have different abilities of DI extraction. When the number of classes is increasing, some DI components, such as B-DI, can keep relatively stable, while others, such as A-DI, lessen sharply. Even to an excellent FEM which can almost make full use of a certain DI component, if this component only occupies slight part of DI, the recognition still dissatisfies us, so rational selection and utilization of DI is vital in radar HRRP target recognition. Usually, different recognition styles may lead to different DI selections and utilizations, but we are accustomed to carrying out a recognition process from the standpoint of a certain spectator who seems "out of this collectivity". We define this recognition style as passive recognition. Admittedly, passive recognition suffers from partial loss of B-DI. In order to obtain more B-DI, a new recognition style called active recognition is proposed in which each class is personified to perform recognizing behavior on behalf of her related target [34].

All in all, DI is the most important factor which directly determines the final recognition result, nevertheless it is always neglected by the fact that it has categories and each category has limited capacity. In this paper, sorted by DI extraction area, DI selection standpoint and recognition style, there are three proposed DI extraction models, i.e., PGA, PIB and AIB[1]. Due to the huge storage requirement and computation burden in radar HRRP target recognition, some computational analysis is provided in the experiment. Additionally, topological diagram is adopted for DI analysis [35], and 1-NN ruler is applied for template match [29].

The rest is organized as follows. In Section 2, we proceed to delve into DI analysis, and three fundamental DI extraction models are proposed, i.e., PGA, PIB and AIB. In Section 3, we conduct GDA into the models and two GDA variations come forth, i.e., PIB-based GDA (PIB-GDA) and AIB-based GDA (AIB-GDA). In Section 4, three recognition processes are designed corresponding to the three DI extraction models. In Section 5, a seven-simulated-plane system and a three-measured-plane system are offered to evaluate the performances. Finally, some conclusions are made in Section 6.

2 Discriminant Information Analysis

Throughout this paper, we assume that the given training HRRP space $\{\mathbf{X}|\mathbf{x}_i, i=1,2,\cdots M\}$ with M HRRPs, and each HRRP is represented as a n-dimensional real column vector. Let g be the total number of classes, m_ξ be the ξ^{th} class' HRRP number, $\{\mathbf{X}_\xi|\mathbf{x}_{\xi,j}, j=1,2,\cdots m_\xi\}$ denote the ξ^{th} class' HRRP subset, and $\mathbf{m}$ be the HRRP number vector, thus we have $\mathbf{m}=\begin{bmatrix} m_1 & m_2 & \cdots & m_g \end{bmatrix}$, $M=\sum_{\xi=1}^{g} m_\xi$ and $\mathbf{X}=\begin{bmatrix} \mathbf{X}_1 & \mathbf{X}_2 & \cdots & \mathbf{X}_g \end{bmatrix}$. The details of HRRP datasets for experiments are offered in Section 5. All the implementations were based on MATLAB 7.1 and performed on a 3.06-GHz Pentium(R)-4 machine which runs Windows XP operation system and has 1-GB EMS memory.

When a process is difficult to understand but can be vividly described by a function, note that this function can't be used for calculation, so we define it as the abstract function of this process. When an algorithm needs many complicated formulas to demonstrate its calculation process, usually, a single function can be used to represent that algorithm, and we define it as synthesis function of that algorithm.

[1] PGA is defined as the DI extraction model in which A-DI is extracted from a general viewpoint and used for passive recognition. PIB is defined as the DI extraction model in which B-DI is extracted from the standpoints of individual classes and used for passive recognition. AIB is defined as the DI extraction model in which B-DI is also extracted from the standpoints of individual classes but used for active recognition.

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2.1 Definition and Analysis

HRRP feature information is defined as the information that is contained in HRRPs and can be used to describe the characters of its related class, including, but not limited to, size and scatter distribution. According to the definition, DI can be considered as a subset of feature information, and doesn't include noise and other useless or harmful information.

2.1.1 Components of DI

In this paper, a simple DI structure is presented in which three fundamental components, i.e., absolute, relative and futile components, are defined according to their different discriminant abilities. Given a system with g classes, absolute DI component is this kind of DI which belongs to only one class, and can be used to discriminate its related class from all the others, while futile DI component belongs to all the classes, and can't be used to discriminate any class from others. Relative component is defined as the rest which excludes the absolute and futile components. Let G_ξ, $G_{a,\xi}$, $G_{f,\xi}$ and $G_{r,\xi}$, respectively, denote class ξ's DI aggregate and her absolute, futile and relative components, thus they are given by

$$\begin{cases} G_{a,\xi} = G_\xi - \bigcup_{i\in D(\xi,g)} \left(G_\xi \cap G_i\right) \\ G_{f,\xi} = \bigcap_{j=1}^{g} G_j \\ G_{r,\xi} = G_\xi - \left(G_{a,\xi} \cup G_{f,\xi}\right) = \bigcup_{\gamma\in D(\xi,g)} G_{r,\xi,\gamma} \end{cases}, \quad (\xi = 1,2,\cdots,g) \tag{1}$$

where $G_{r,\xi,\gamma}$ is class ξ's relative DI component obtained from class γ's standpoint, and $D(\xi,g)$ is a subset function for class selecting. They are given by

$$\begin{cases} G_{r,\xi,\gamma} = \begin{cases} G_{r,\xi} & \gamma = \xi \\ G_\xi - G_{a,\xi} - \left(G_\xi \cap G_\gamma\right) & \gamma \in D(\xi,g) \end{cases} \\ D(\xi,g) = \{1,2,\cdots,\xi-1,\xi+1,\cdots,g-1,g\} \end{cases}, \quad (\xi = 1,2,\cdots,g) \tag{2}$$

For example, as shown in Fig. 1 (a, b), there are two topological diagrams to demonstrate the DI components of a three-class system. From Fig. 1 (a), we can discern the absolute, relative and futile DI components clearly. Due to the close-set property between class 2 and 3, compared with $G_2 \cap G_3$, their absolute and relative DI components, i.e., $G_{a,2}$, $G_{r,2,3}$, $G_{a,3}$ and $G_{r,3,2}$, are all relatively small, which can apparently increase the recognition difficulty between class 2 and 3. Let's consider the DI components from class 1's standpoint. As shown in Fig. 1 (b), the absolute and relative components, i.e., $G_{a,1}$ and $G_{r,1}$, are both beneficial to her discrimination, while the futile component $G_{f,1}$ is useless to her discrimination. If class 1's feature information contains the element of $G_{a,2}$, $G_{a,3}$ or $G_2 \cap G_3 - G_{f,1}$, obviously, it is harmful to her discrimination, so we called it bad DI component from class 1's standpoint.

2.1.2 Types of DI

On account of different roles in application, there are two fundamental DI types, i.e., A-DI and B-DI. A-DI is defined as the DI subset which can be used to discriminate its related class from all the others, while B-DI is defined as the DI subset which can be used to discriminate its related class from at least one of the others, that is,

$$\begin{cases} G_{A,\xi} = G_{a,\xi} \\ G_{B,\xi} = G_{a,\xi} \cup G_{r,\xi} = \bigcup_{k\in D(\xi,g)} G_{B,\xi,k} \end{cases}, \quad (\xi = 1,2,\cdots,g) \tag{3}$$

where $G_{A,\xi}$ denotes class ξ's A-DI, $G_{B,\xi}$ denotes class ξ's B-DI, and $G_{B,\xi,\gamma}$ denotes class ξ's B-DI subset from the standpoint of class γ, which is given by

$$G_{B,\xi,\gamma} = \begin{cases} G_{B,\xi} & \gamma = \xi \\ G_\xi - \left(G_\xi \cap G_\gamma\right) & \gamma \in D(\xi,g) \end{cases}. \quad (\xi = 1,2,\cdots,g) \tag{4}$$

Hence we can conclude that, in mathematics, one class' B-DI obtained from her own standpoint is equivalent to the union obtained from the standpoints of all other individuals. As indicated by (3), since A-DI is equal to absolute DI component, B-DI can be considered as the union of A-DI and relative DI component. Actually, A-DI is the most usable DI, which always receives intensity attention from HRRP-based RATA communities [17]–[23], [29], [38]. Compared with A-DI, the relative DI component can't be used to discriminate its class from all the others, but at least, it can be used to discriminate its related class from one of the others. As a result, it decreases the quantity of discriminant classes in some sense, and reduces the recognition difficulty to some extent, so it is also beneficial to discrimination. Furthermore, as analyzed in Section 5.2.1, making use of B-DI doesn't increase, or acceptably increases, or even decreases the storage requirement and computation burden.

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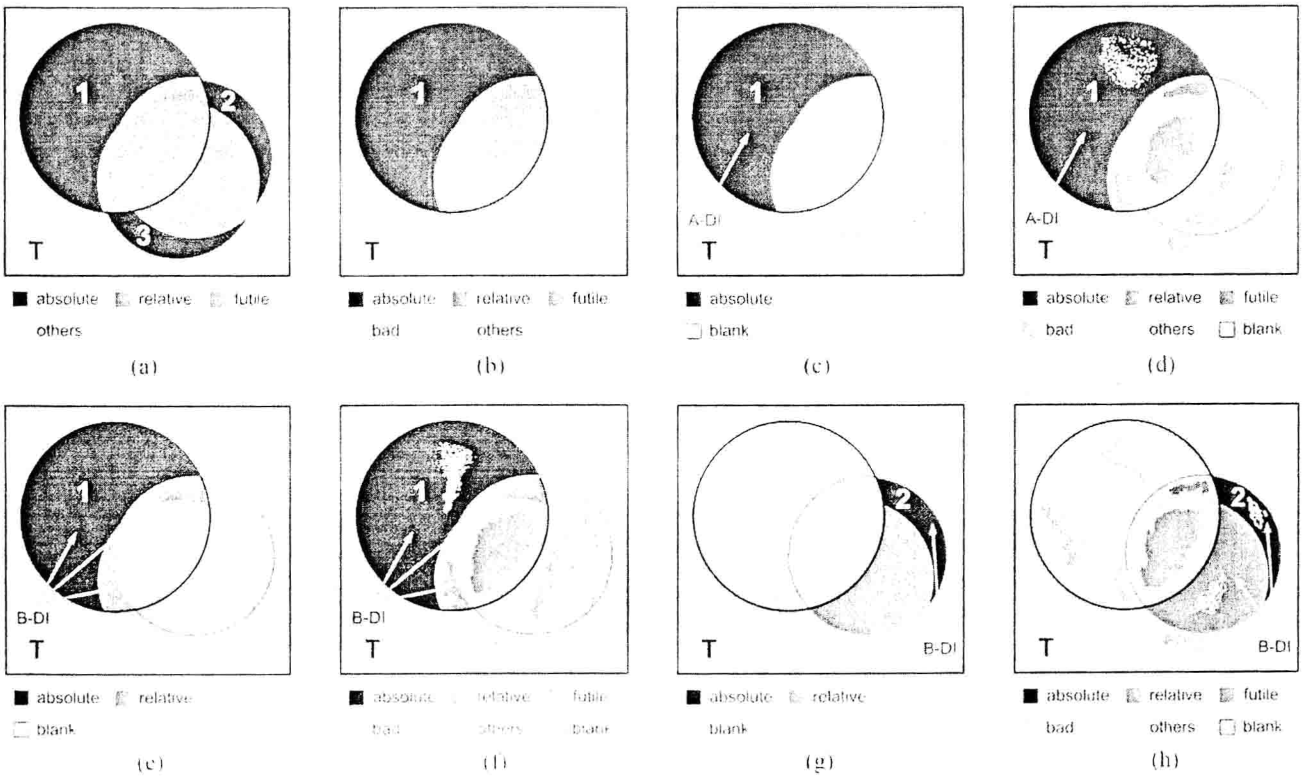

Fig. 1: Using topological diagrams to demonstrate the DI components of a 3-class system. (a) DI components of three classes in theory. (b) DI components of class 1 in theory. (c) PGA: class 1's theoretical A-DI from a general viewpoint. (d) PGA: class 1's practical DI components from a general viewpoint. (e) PIB or AIB: class 1's theoretical B-DI from class 1's standpoint. (f) PIB or AIB: class 1's practical DI components from class 1's standpoint. (g) AIB: class 2's theoretical B-DI from class 1's standpoint. (h) AIB: class 2's practical DI components from class 1's standpoint. (Practical DI components denote the DI components which are obtained by a certain FEM. These sketch maps are just used to demonstrate DI analysis, and aren't obtained from the measured or simulated experiments.)

2.1.3 Extraction of DI

Compared with MI that can be obtained via calculating probability density, differential entropy and other related parameters [1]–[6], it is difficult to obtain a certain pure DI component from original dataset, but some FEMs can be designed to obtain the special FTs which contain the appointed DI components, and therefore, their abilities of DI extraction can be estimated by the recognition performance. Nevertheless, from the viewpoint of statistics, it is impossible or impractical for a certain FEM to obtain the FTs which contain the whole selected DI components, and moreover, it is reasonable for the FTs containing other DI components, or even other useless or harmful information, so an abstract function for DI extraction can be defined by

$$\begin{cases}\{\Theta_{a,\xi},\Theta_{r,\xi},\Theta_{f,\xi},O_\xi\}_{FT} = \Re^{\wp}\left(\mathbf{X}_\xi, G_{\Omega,\xi}\right) \\ \Theta_{\tau,\xi}\subset G_{\tau,\xi} \qquad (\tau = \mathrm{a, r, f})\end{cases} \qquad (\xi=1,2,\cdots,g) \tag{5}$$

where $\Re^{\wp}\left(\mathbf{X}_\xi, G_{\Omega,\xi}\right)$ denotes an abstract function for FEM $\Re$ to obtain class ξ's DI components corresponding to a given DI extraction model $\wp$, Ω denotes the DI type, such as A-DI and B-DI, and $\{\Theta_{a,\xi},\Theta_{r,\xi},\Theta_{f,\xi},O_\xi\}_{FT}$ is defined as the information aggregate in class ξ's FTs, here $\Theta_{a,\xi}$, $\Theta_{r,\xi}$, $\Theta_{f,\xi}$ and O_ξ, respectively, denote absolute, relative, futile DI components and other information obtained by FEM $\Re$. Note that, by (5), FEM $\Re$ aims to class ξ's theoretical $G_{\Omega,\xi}$, but in practice it obtains $\{\Theta_{a,\xi},\Theta_{r,\xi},\Theta_{f,\xi},O_\xi\}_{FT}$.

2.2 DI Extraction Models

Based on the analysis above, we can find that, more DI components may lead to more DI extraction area, and better FEM for a certain DI component can obtain more DI of this kind. So there are two main aspects to deal with it, that is to say, by what model to design DI extraction, and by which FEM to externalize the model. In this subsection, we mainly

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Table 1: Abbreviative notations of three DI extraction models

abbreviative notation	recognition style	selection standpoint	extraction area
PGA	passive	general	A-DI
PIB	passive	individual	B-DI
AIB	active	individual	B-DI

concern with the models, and their actualizations are offered in Section 3. According to various DI extraction areas and selection standpoints, there are three fundamental DI extraction models, i.e., PGA, PIB and AIB, here the DI extraction area is defined as the total scale of the selected DI components that the model aims to obtain. Showing in Table 1 is the three abbreviative notations corresponding to the three DI extraction models, which are sorted by DI extraction area, DI selection standpoint and recognition style.

2.2.1 PGA

PGA is defined as the DI extraction model in which A-DI is extracted from a general viewpoint of collectivity and used for passive recognition. According to (5), its abstract DI extraction function is

$$\begin{cases} \left\{\Theta_{\mathrm{a},\xi},\Theta_{\mathrm{r},\xi},\Theta_{\mathrm{f},\xi},O_{\xi}\right\}_{\mathrm{FT}} = \Re^{\mathrm{PGA}}\left(\mathbf{X}_{\xi},G_{\mathrm{A},\xi}\right) \\ \Theta_{\mathrm{A},\xi}^{\mathrm{PGA}} = \Theta_{\mathrm{a},\xi} \subset G_{\mathrm{A},\xi} \end{cases} \quad (\xi = 1,2,\cdots,g) \tag{6}$$

where $\Theta_{\mathrm{A},\xi}^{\mathrm{PGA}}$ denotes class ξ 's practical A-DI extracted by FEM $\Re$. For example, there are two sketch maps for PGA in Fig. 2 (c, d), from which class 1's theoretical A-DI and practical DI components are demonstrated, respectively, by two topological diagrams.

One view worth pointing out is that, PGA prevails in statistical pattern recognition despite the inefficiency of DI extraction and utilization innately exiting in it. With respect to the FTs extracted by a FEM under certain global optimization criterion, they can be statistically discriminated on each projection axis of feature extraction [28], [29], so from the viewpoint of statistics, each single value in them can be used to discriminate its class from all the others. According to Section 2.1.2, the value contains the element of A-DI, and the FTs contain the practical A-DI. During past years, there were many statistical FEMs proposed for A-DI extraction by PGA mode, such as LDA, GDA, the Direct-LDA (DLDA), the Modified GDA (MGDA), the Kernel Direct Discriminant Analysis (KDDA), etc [2], [5], [17], [22]–[27]. Even though these FEMs have been proven successful in many applications, their usages are still a bit inanimate, that is, the prevalent applications of them were usually designed to obtain the A-DI among all classes while neglecting the B-DI between two random classes, thereby potentially losing the relative DI components and possibly resulting in a dissatisfied recognition performance.

Another view worth emphasizing is that, PGA is crag-fast in multi-target recognition. Although PGA originally aims to solve a multi-class discriminant problem, but with the number of classes increasing, the content of A-DI reduces urgently in theory, thereby sharply increasing the difficulty and uncertainness of information extraction in practice. The detailed analysis is offered in Section 2.3 by a simple mathematical model.

2.2.2 PIB

Admittedly, A-DI can be used to discriminant one class from all the others, but it only occupies part of DI, and can be considered as a subset of B-DI, so making use of B-DI may perform better than A-DI does. In order to obtain B-DI, a new DI extraction model called PIB is proposed in which each class' B-DI is selected from her own standpoint and also used for passive recognition. The abstract DI extraction function is given by

$$\begin{cases} \left\{\Theta_{\mathrm{a},\gamma},\Theta_{\mathrm{r},\gamma},\Theta_{\mathrm{f},\gamma},O_{\gamma}\right\}_{\mathrm{FT}} = \Re_{\gamma}^{\mathrm{PIB}}\left(\mathbf{X}_{\xi},G_{\mathrm{B},\xi,\gamma}\right) \quad \text{s.t.}\ \xi=\gamma \\ \Theta_{\mathrm{B},\gamma}^{\mathrm{PIB}} = \left(\Theta_{\mathrm{a},\gamma}\cup\Theta_{\mathrm{r},\gamma}\right) \subset G_{\mathrm{B},\gamma} \end{cases} \quad (\gamma=1,2,\cdots,g) \tag{7}$$

where $\Theta_{\mathrm{B},\gamma}^{\mathrm{PIB}}$ denotes class γ 's practical B-DI obtained by FEM $\Re$ from her own standpoint. Showing in Fig. 1 (e, f) are the two sketch maps for PIB, in which class 1's theoretical B-DI and practical DI components are demonstrated by two topological diagrams respectively.

Although (7) can be considered as an intuitive notation for PIB in theory, but it is not easy to realize in application. Since one class' B-DI obtained from her own standpoint is equivalent to the union obtained from the standpoints of all the others, a variation for PIB is provided by

$$\begin{cases} \begin{cases} \left\{\Theta_{\mathrm{a},\gamma,\xi},\Theta_{\mathrm{r},\gamma,\xi},\Theta_{\mathrm{f},\gamma,\xi},O_{\gamma,\xi}\right\}_{\mathrm{FT}} = \Re_{\xi}^{\mathrm{PIB}}\left(\mathbf{X}_{\gamma},G_{\mathrm{B},\gamma,\xi}\right) \\ \Theta_{\mathrm{B},\gamma,\xi}^{\mathrm{PIB}} = \left(\Theta_{\mathrm{a},\gamma,\xi}\cup\Theta_{\mathrm{a},\gamma,\xi}\right) \subset G_{\mathrm{B},\gamma,\xi} \end{cases} \\ \Theta_{\mathrm{B},\gamma}^{\mathrm{PIB}} = \bigcup_{k\in D(\gamma,g)} \Theta_{\mathrm{B},\gamma,k}^{\mathrm{PIB}} \subset \bigcup_{k\in D(\gamma,g)} G_{\mathrm{B},\gamma,k} \Leftrightarrow G_{\mathrm{B},\gamma} \end{cases} \quad \left(\xi\in D(\gamma,g),\ \ \gamma=1,2,\cdots,g\right) \tag{8}$$

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where $\Theta^{\mathrm{PIB}}_{\mathrm{B},\gamma,\xi}$ denotes class γ 's practical B-DI obtained by FEM $\Re$ from class ξ 's standpoint.

Let's analyze the DI extraction areas of PGA and PIB. According to the definitions of A-DI and B-DI, although the DI extraction area of PIB is larger than that of PGA, but the quality of PGA's DI extraction area is higher than PIB's. In some sense, the DI extraction areas of PGA and PIB can be considered as two different reflections of DI, that is, PGA emphasizes the quality while PIB prefers to the size: PGA emphasizes common differentia among all classes while PIB prefers to individual differentia between two random classes.

2.2.3 AIB

Compared with PIB, individual AIB also aims for B-DI, but all class' B-DI is selected from one class' standpoint and used for active recognition. Here is the abstract DI extraction function of individual AIB:

$$\begin{cases} \begin{cases} \{\Theta_{\mathrm{a},\gamma},\Theta_{\mathrm{r},\gamma},\Theta_{\mathrm{f},\gamma},O_{\gamma}\}_{\mathrm{FT}} = \Re^{\mathrm{PIB}}_{\gamma}(\mathbf{X}_{\xi},G_{\mathrm{B},\xi,\gamma}) \\ \Theta^{\mathrm{AIB}}_{\mathrm{B},\xi,\gamma} = \Theta^{\mathrm{AIB}}_{\mathrm{B},\gamma} = (\Theta_{\mathrm{a},\gamma}\cup\Theta_{\mathrm{r},\gamma}) \subset G_{\mathrm{B},\gamma} \end{cases} & \xi=\gamma \\ \begin{cases} \{\Theta_{\mathrm{a},\xi,\gamma},\Theta_{\mathrm{r},\xi,\gamma},\Theta_{\mathrm{f},\xi,\gamma},O_{\xi,\gamma}\}_{\mathrm{FT}} = \Re^{\mathrm{AIB}}_{\gamma}(\mathbf{X}_{\xi},G_{\mathrm{B},\xi,\gamma}) \\ \Theta^{\mathrm{AIB}}_{\mathrm{B},\xi,\gamma} = (\Theta_{\mathrm{a},\xi,\gamma}\cup\Theta_{\mathrm{a},\xi,\gamma}) \subset G_{\mathrm{B},\xi,\gamma} \end{cases} & \xi\in D(\gamma,g) \end{cases}$$

$$(\gamma=1,2,\cdots,g), \tag{9}$$

where $\Theta^{\mathrm{AIB}}_{\mathrm{B},\xi,\gamma}$ denotes class ξ 's practical B-DI obtained by FEM $\Re$ from class γ 's standpoint. For example, showing in Fig. 1 (e–h) are the four sketch maps from class 1's standpoint, in which class 1 and class 2's theoretical and practical DI components are demonstrated, respectively, by four diagrams.

Let's consider class ξ 's DI extraction areas from different individual standpoints. From her own standpoint, the DI extraction area is $G_{\mathrm{B},\xi}$, while from class γ 's standpoint, the DI extraction area is $G_{\mathrm{B},\xi,\gamma}$. We compare the two areas by

$$\begin{cases} G_{\mathrm{B},\xi,\gamma} = G_{\mathrm{B},\xi} & \gamma=\xi \\ G_{\mathrm{B},\xi,\gamma} \subset G_{\mathrm{B},\xi} & \gamma\in D(\xi,G) \end{cases} \quad (\gamma=1,2,\cdots,g), \tag{10}$$

so we can find that the DI extraction area of PIB is larger than that of individual AIB, that is,

$$\begin{cases} G^{\mathrm{AIB}}_{\mathrm{B,I},\gamma} \subset G^{\mathrm{PIB}}_{\mathrm{B}} \\ \text{s.t.} \begin{cases} G^{\mathrm{PIB}}_{\mathrm{B}} = \bigcup_{i=1}^{g} G_{\mathrm{B},i} \\ G^{\mathrm{AIB}}_{\mathrm{B,I},\gamma} = \bigcup_{j=1}^{g} G_{\mathrm{B},j,\gamma} \end{cases} \end{cases} \quad (\gamma=1,2,\cdots,g), \tag{11}$$

where G^{PIB}_{B} denotes PIB's total DI extraction area, and $G^{\mathrm{AIB}}_{\mathrm{B,I},\gamma}$ denotes individual AIB's total DI extraction area from class γ 's standpoint.

An explain to this phenomenon is given as that, in individual AIB, class γ is personified on behalf of her related class, so there are some individual bias and selfness inevitably existing in her judgement [34]. It is reasonable for her to select the B-DI relating to her class while neglecting the rest. For example, as shown in Fig. 1 (g), from class 1's standpoint, class 2's B-DI subset $G_{\mathrm{B},2,1}$ is selected while $G_{\mathrm{B},2,3}-G_{\mathrm{A},2}$ is abandoned. In summary, individual AIB's DI extraction area is smaller than PIB's, besides which there are some personal biases in individual AIB, so by the same FEM, PIB should perform better than individual AIB does.

Fortunately, not only is AIB designed for individual discrimination, but also for global discrimination. Let's analyze global AIB's total DI extraction area $G^{\mathrm{AIB}}_{\mathrm{B}}$ by

$$\begin{aligned} G^{\mathrm{AIB}}_{\mathrm{B}} &= \bigcup_{k=1}^{g} G^{\mathrm{AIB}}_{\mathrm{B,I},k} = \bigcup_{k=1}^{g}\left(\bigcup_{i=1}^{g} G_{\mathrm{B},i,k}\right) \\ &= \bigcup_{i=1}^{g}\left(\bigcup_{k=1}^{g} G_{\mathrm{B},i,k}\right) = \bigcup_{i=1}^{g}\left(\bigcup_{k\in D(\xi,g)} G_{\mathrm{B},i,k}\right), \\ &= G^{\mathrm{PIB}}_{\mathrm{B}} \end{aligned} \tag{12}$$

that is to say further, global AIB is equivalent to PIB in theory.

2.3 Comparison of Information Content

As proven above, since global AIB is equivalent to PIB in theory, we only analyze the change of DI content in the three models, i.e., PGA, PIB and individual AIB. Due to the range and diversity of the targets in real applications, there are many formidable obstacles to estimate their DI performances, but an ideal mathematical model can be designed to test the general performance. In this paper, a mathematical model is provided in which each class has the same statistical property and can be considered as an isotropy subset:

$$\begin{cases} f\left(\bigcap_{i=1}^{k} G_{\xi_i}\right) = \rho(1-\sigma)^{k-1} \\ f\left(\bigcup_{i=1}^{k} G_{\xi_i}\right) = \rho\left(1+\sigma\dfrac{1-\sigma^{k-1}}{1-\sigma}\right) \end{cases} \quad \begin{pmatrix} k=1,2,\cdots,g \\ 0<\sigma<1 \end{pmatrix}$$

$$\text{s.t.} \quad \begin{cases} \xi_1,\xi_2,\cdots\xi_k \in \{1,2,\cdots g\} \\ \text{and} \quad \xi_1 \neq \xi_2 \neq \cdots \neq \xi_k \end{cases}, \tag{13}$$

where $f(*)$ is defined as an abstract function to *obtain the DI content, ρ denotes the original infor-*

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mation content of each class, and σ denotes the utilization rate of DI between two classes.

Under this suppositional model, the content of $G_{\mathrm{A},\xi}$, $G_{\mathrm{B},\xi}$ and $G_{\mathrm{B},\xi,\gamma}$ can be obtained by

$$\begin{cases} \rho_{\mathrm{A},\xi} = f\left(G_{\mathrm{A},\xi}\right) = \rho\sigma^{g-1} \\ \rho_{\mathrm{B},\xi} = f\left(G_{\mathrm{B},\xi}\right) = \rho\left(1-(1-\sigma)^{g-1}\right) \\ \rho_{\mathrm{B},\xi,\gamma} = f\left(G_{\mathrm{B},\xi,\gamma}\right) \qquad\qquad (\xi = 1,2,\cdots,g), \\ \quad = \begin{cases} \rho\left(1-(1-\sigma)^{g-1}\right) & \gamma = \xi \\ \rho\sigma & \gamma \in D(\xi,g) \end{cases} \end{cases} \tag{14}$$

where $\rho_{\mathrm{A},\xi}$, $\rho_{\mathrm{B},\xi}$ and $\rho_{\mathrm{B},\xi,\gamma}$, respectively, denote the information content of $G_{\mathrm{A},\xi}$, $G_{\mathrm{B},\xi}$ and $G_{\mathrm{B},\xi,\gamma}$.

Due to the same mathematical model that the three DI extraction models get involved with, the influence of the original information content can be overlooked. Suppose that ρ is equal to 1, then the average usable DI contents of the three models can be estimated by

$$\begin{cases} \rho_{\mathrm{A}}^{\mathrm{PGA},g} = \dfrac{1}{g}\sum_{k=1}^{g} \rho_{\mathrm{A},k} = \sigma^{g-1} \\ \rho_{\mathrm{B}}^{\mathrm{PIB},g} = \dfrac{1}{g}\sum_{k=1}^{g} \rho_{\mathrm{B},k} = 1-(1-\sigma)^{g-1} \\ \rho_{\mathrm{B},\mathrm{I}}^{\mathrm{AIB},g} = \dfrac{1}{g}\sum_{k=1}^{g} \rho_{\mathrm{B},k,\gamma} = \dfrac{1-(1-\sigma)^{g-1}}{g} + \dfrac{g-1}{g}\sigma \end{cases}$$
$$(\gamma = 1,2,\cdots,g), \tag{15}$$

where $\rho_{\mathrm{A}}^{\mathrm{PGA},g}$, $\rho_{\mathrm{B}}^{\mathrm{PIB},g}$ and $\rho_{\mathrm{B},\mathrm{I}}^{\mathrm{AIB},g}$, respectively, denote the appointed DI content of PGA, PIB and AIB.

In some sense, pattern recognition can be considered as to solve a comparison and match problem, so the quality of DI is more important than its content [28], [29]. But in application, it is a bit difficult to extract the relatively slight DI components from a huge dataset, which not only improves the extraction difficulty, but also depresses the information accuracy. As demonstrated by (15), with the number of classes increasing, in terms of DI content, PIB can almost make full use of DI, individual AIB also keeps optimistically stable, while PGA suffers from an exponentially decay.

3 Model Actualization Analysis

Generally, in pattern recognition, feature extraction can be considered as the process of deriving useful DI from some original signals, here DI has a more compact representation and can be adopted for a certain task, such as template match and target recognition. As aforementioned in Section 2.1.3, FT can be considered as a carrier of DI. Since it is difficult to extract pure DI component from the original datasets, a certain FEM $\Re$ can be applied to obtain the special FTs which contain the designed DI components. As a nonlinear extension of LDA via kernel trick, GDA has been proved often achieving better recognition performance than other nonlinear methods due to the perfect capability of DI extraction [25], [26], so we apply it in the three DI extraction models as the fundamental discriminant analysis unit, and accordingly, two new GDA variations come forth, i.e., PIB-GDA and AIB-GDA.

3.1 Application of GDA in PGA

Given two HRRP subspaces $\mathbf{X}_w$ and $\mathbf{X}_v$, we define the kernel function $\mathrm{k}\left(\mathbf{x}_{w,i}, \mathbf{x}_{v,j}\right)$ corresponding to a given nonlinear mapping Φ by

$$\mathrm{k}\left(\mathbf{x}_{w,i}, \mathbf{x}_{v,j}\right) = \left\langle \Phi\left(\mathbf{x}_{w,i}\right), \Phi\left(\mathbf{x}_{v,j}\right)\right\rangle. \quad (w,v = 1,2,\cdots g) \tag{16}$$

Note that there are many kernel functions but each one must meet Mercer condition [29]–[32]. We apply Gaussian kernel function for kernel calculating by

$$\begin{cases} \varphi_{i,j} = \mathrm{k}\left(\mathbf{x}_{w,i}, \mathbf{x}_{v,j}\right) = \exp\left(-\left\|\mathbf{x}_{w,i} - \mathbf{x}_{v,j}\right\|^2 / \sigma^2\right) \\ \mathbf{K}_{w,v} = \left(\varphi_{i,j}\right)_{\substack{i=1,2,\cdots,m_w \\ j=1,2,\cdots,m_v}} \triangleq \mathbb{k}\left(\mathbf{X}_w, \mathbf{X}_v\right) \end{cases}, \quad (w,v = 1,2,\cdots g) \tag{17}$$

where $\mathbf{K}_{w,v}$ denotes the kernel matrix of $\mathbf{X}_w$ by $\mathbf{X}_v$, and the symbol $\mathbb{k}(*,*)$ denotes the kernel synthesis function. In this paper, we suppose that σ^2 is equal to 0.5.

As explored in [25], GDA is originally designed to solve a multi-class discriminant problem for passive recognition. The essence of GDA is to find an optimal transformation by maximizing the between-class distance and minimizing the within-class distance, thereby obtaining the FTs which contain the practical A-DI. According to a variant of Fisher's kernel criterion variant [29]–[31], it aims to solve an optimization problem:

$$J(\mathbf{u}_{\mathrm{opt}}) = \arg\max_{\mathbf{u}} \frac{\mathbf{u}^{\mathrm{T}}(\mathbf{QWQ})\mathbf{u}}{\mathbf{u}^{\mathrm{T}}(\mathbf{QQ})\mathbf{u}}, \tag{18}$$

where the kernel symmetric matrix $\mathbf{Q}$ is obtained by $\mathbf{Q}=\mathbf{K}-\mathbf{1}_M\mathbf{K}-\mathbf{K}\mathbf{1}_M+\mathbf{1}_M\mathbf{K}\mathbf{1}_M$, and the block diagonal matrix $\mathbf{W}=\mathrm{diag}(\mathbf{1}_{m_1},\mathbf{1}_{m_2}\cdots,\mathbf{1}_{m_g})$, here the mean value matrix $\mathbf{1}_\tau$ is defined as a $\tau\times\tau$ matrix with terms all equal to $1/\tau$, and the kernel matrix $\mathbf{K}$ is given by $\mathbf{K}=\Bbbk(\mathbf{X},\mathbf{X})$.

Let's rank the coefficient vectors $\mathbf{u}_i$ conforming to their related cost values $J(\mathbf{u}_i)$ in descending order, and select the front $g-1$ ones as the Feature Extraction Subspace (FES) $\mathbf{U}$. Then for a given HRRP $\mathbf{y}$, its feature vector can be obtained by

$$\mathbf{z}=\left(\Bbbk(\mathbf{y},\mathbf{X})\times\mathbf{U}\right)^{\mathrm{T}}. \tag{19}$$

where z is a $(g-1)$-dimensional column vector, which contains $\mathbf{y}$'s A-DI and can be considered as $\mathbf{y}$'s feature vector.

Now according to (16)–(19), we can acquire the FT matrix $\mathbf{A}^{\mathrm{PGA}}$ and the feature matrix $\mathbf{Z}^{\mathrm{PGA}}$ by

$$\begin{cases}\mathbf{A}^{\mathrm{PGA}}=\begin{bmatrix}\mathbf{A}_1^{\mathrm{PGA}} & \mathbf{A}_2^{\mathrm{PGA}} & \cdots & \mathbf{A}_g^{\mathrm{PGA}}\end{bmatrix}\\ \left\{\mathbf{A}^{\mathrm{PGA}},\mathbf{Z}^{\mathrm{PGA}}\right\}\triangleq\mathbb{S}_{\mathrm{GDA}}\left(\mathbf{Y},\mathbf{X},\mathbf{m}\right)\end{cases}. \tag{20}$$

where $\mathbb{S}_{\mathrm{GDA}}\left(\mathbf{Y},\mathbf{X},\mathbf{m}\right)$ is defined as the GDA synthesis function of PGA for $\mathbf{X}$ and $\mathbf{Y}$ to obtain their feature matrixes $\mathbf{A}^{\mathrm{PGA}}$ and $\mathbf{Z}^{\mathrm{PGA}}$, $\left\{\mathbf{A}^{\mathrm{PGA}},\mathbf{Z}^{\mathrm{PGA}}\right\}$ denotes an aggregate with two matrix elements ($\mathbf{A}^{\mathrm{PGA}}$ and $\mathbf{Z}^{\mathrm{PGA}}$) in it, and $\mathbf{A}^{\mathrm{PGA}}$'s subset $\mathbf{A}_\xi^{\mathrm{PGA}}$ is the ξ^{th} $(\xi=1,2,\cdots,g)$ class' FT matrix. Note that the matrix $\mathbf{Y}$ only denotes a given HRRP subset which may be comprised of some training HRRPs or test ones, and of course $\mathbf{Y}$ can be a one vector matrix when it contains only one HRRP.

3.2 Application of GDA in PIB

As an extension version of Kernel Fisher Discriminant Analysis (KFDA) [33], not only can GDA be designed for multi-class discrimination, but also used as a KFDA variation to solve the two-class pattern recognition problem. According to Section 2.1, B-DI can be considered as the DI components between two random classes, so we apply GDA to obtain B-DI by

$$\begin{cases}\begin{cases}\mathbf{X}_{\gamma,\xi}=\begin{bmatrix}\mathbf{X}_\gamma & \mathbf{X}_\xi\end{bmatrix}\\ \mathbf{m}_{\gamma,\xi}=\begin{bmatrix}m_\gamma & m_\xi\end{bmatrix}\end{cases}\\ \left\{\mathbf{B}_{\gamma,\xi},\mathbf{Z}_{\gamma,\xi}\right\}=\mathbb{S}_{\mathrm{GDA}}\left(\mathbf{Y},\mathbf{X}_{\gamma,\xi},\mathbf{m}_{\gamma,\xi}\right)\end{cases}, \tag{21}$$
$$\left(\xi\in D(\gamma,g),\quad \gamma=1,2,\cdots,g\right)$$

where $\mathbf{Z}_{\gamma,\xi}$ denotes $\mathbf{Y}$'s feature matrix discriminated by class γ and ξ. Note that $\mathbf{Z}_{\gamma,\xi}$ is only a row vector and each element denotes a feature value of the related HRRP.

Let's consider GDA for two-class discriminant analysis. The two classes are related to each other and can be discriminated on a feature extraction axis. According to (21), when $\mathbf{Y}$ is equal to $\mathbf{X}_\gamma$, its feature matrix $\mathbf{Z}_{\gamma,\xi}$ contains the practical B-DI $\Theta_{\mathrm{B},\gamma,\xi}^{\mathrm{PIB}}$, which is class γ's B-DI obtained by GDA from class ξ's standpoint, and vice versa. In terms of optimization, when $\mathbf{Y}$ doesn't belong to class γ or ξ, the DI component in $\mathbf{Z}_{\gamma,\xi}$ is defective, and moreover, some additional redundant information enters into $\mathbf{Z}_{\gamma,\xi}$, thereby decreasing the discriminant efficiency. Now we arrange $\mathbf{Z}_{\gamma,\xi}$ from different individual standpoints by

$$\mathbf{Z}_\gamma^{\mathrm{PIB}}=\begin{bmatrix}\mathbf{Z}_{1,\gamma}{}^{\mathrm{T}} & \mathbf{Z}_{2,\gamma}{}^{\mathrm{T}} & \cdots & \mathbf{Z}_{\gamma-1,\gamma}{}^{\mathrm{T}} & \mathbf{Z}_{\gamma+1,\gamma}{}^{\mathrm{T}} & \cdots & \mathbf{Z}_{g,\gamma}{}^{\mathrm{T}}\end{bmatrix}^{\mathrm{T}}, \tag{22}$$
$$(\gamma=1,2,\cdots,g)$$

where $\mathbf{Z}_\gamma^{\mathrm{PIB}}$ is $\mathbf{Y}$'s feature matrix from all other classes' standpoints except class γ.

In accordance with the analysis in Section 2.2, $\mathbf{Z}_\gamma^{\mathrm{PIB}}$ can be considered as $\mathbf{Y}$'s feature matrix from class γ's standpoint. When $\mathbf{Y}$ is equal to $\mathbf{X}_\gamma$, its feature matrix $\mathbf{Z}_\gamma^{\mathrm{PIB}}$ becomes class γ's FT matrix $\mathbf{A}_\gamma^{\mathrm{PIB}}$, which contains the practical B-DI $\Theta_{\mathrm{B},\gamma}^{\mathrm{PIB}}$. Note that $\mathbf{X}_\gamma$ is a subset of $\mathbf{X}$ and can be labeled by $\mathbf{m}$ and γ. According to (21), (22), a GDA synthesis function from class γ's standpoint is given by

$$\left\{\mathbf{A}_\gamma^{\mathrm{PIB}},\mathbf{Z}_\gamma^{\mathrm{PIB}}\right\}\triangleq\mathbb{S}_\gamma^{\mathrm{PIB}}\left(\mathbf{Y},\mathbf{X},\mathbf{m}\right)\quad(\gamma=1,2,\cdots,g), \tag{23}$$

where $\mathbb{S}_\gamma^{\mathrm{PIB}}\left(\mathbf{Y},\mathbf{X},\mathbf{m}\right)$ is defined as PIB's GDA synthesis function from class γ's standpoint, and used for $\mathbf{X}_\gamma$ and $\mathbf{Y}$ to obtain their related feature matrixes $\mathbf{A}_\gamma^{\mathrm{PIB}}$ and $\mathbf{Z}_\gamma^{\mathrm{PIB}}$, here $\mathbf{A}_\gamma^{\mathrm{PIB}}$ is defined as class γ's FT matrix obtained from her own standpoint. As the same goes for PIB, a GDA synthesis function is given by

$$\begin{cases}\begin{cases}\mathbf{A}^{\mathrm{PIB}}=\begin{bmatrix}\mathbf{A}_1^{\mathrm{PIB}} & \mathbf{A}_2^{\mathrm{PIB}} & \cdots & \mathbf{A}_g^{\mathrm{PIB}}\end{bmatrix}\\ \mathbf{Z}^{\mathrm{PIB}}=\begin{bmatrix}\mathbf{Z}_1^{\mathrm{PIB}} & \mathbf{Z}_2^{\mathrm{PIB}} & \cdots & \mathbf{Z}_g^{\mathrm{PIB}}\end{bmatrix}\end{cases}\\ \left\{\mathbf{A}^{\mathrm{PIB}},\mathbf{Z}^{\mathrm{PIB}}\right\}\triangleq\mathbb{S}^{\mathrm{PIB}}\left(\mathbf{Y},\mathbf{X},\mathbf{m}\right)\end{cases}, \tag{24}$$

where $\mathbb{S}^{\mathrm{PIB}}\left(\mathbf{Y},\mathbf{X},\mathbf{m}\right)$ is defined as PIB's GDA synthesis function for $\mathbf{X}$ and $\mathbf{Y}$, respectively, to obtain their feature matrix $\mathbf{A}^{\mathrm{PIB}}$ and $\mathbf{Z}^{\mathrm{PIB}}$ from an overall standpoint. Obviously, to each HRRP, there are g

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feature vectors corresponding to g classes. Note that the total calculation process to obtain $\{\mathbf{A}^{PIB},\mathbf{Z}^{PIB}\}$ is defined as PIB-GDA in this paper.

3.3 Application of GDA in PGA

As described above, by PIB, class γ only obtains her own FTs, so she can't estimate which class a test HRRP belongs to. If each class is personified to perform recognizing behavior on behalf of her related target, what will happen? In order to discriminate a new HRRP, she needs the FTs of all classes so as to match and classify it. But how can she obtain the FTs of all the classes? In this paper, a new model called AIB is proposed in which each class obtains the FTs of all classes from her own standpoint, and of course, the FTs should contain the appointed DI components. Let's consider the FT matrix obtained by (22) from class γ 's standpoint. When $\mathbf{Y}$ is equal to $\mathbf{X}_\xi$, its feature matrix $\mathbf{Z}_\gamma^{PIB}$ becomes class ξ 's FT matrix $\mathbf{A}_{\xi,\gamma}^{AIB}$, which contains the B-DI $\Theta_{B,\xi,\gamma}^{AIB}$ and can be used for template match. By the same, class γ can obtain the FTs of all classes. We construct a GDA synthesis function from class γ 's standpoint by

$$\begin{cases}\mathbf{A}_{1,\gamma}^{AIB}=\left[\mathbf{A}_{1,1,\gamma}^{AIB}\ \mathbf{A}_{1,2,\gamma}^{AIB}\ \cdots\ \mathbf{A}_{1,g,\gamma}^{AIB}\right]\\ \left\{\mathbf{A}_{1,\gamma}^{AIB},\mathbf{Z}_{1,\gamma}^{AIB}\right\}\triangleq\mathbb{S}_{1,\gamma}^{AIB}(\mathbf{Y},\mathbf{X},\mathbf{m})\end{cases}\quad(\gamma=1,2,\cdots,g),\quad(25)$$

where $\mathbb{S}_{1,\gamma}^{AIB}(\mathbf{Y},\mathbf{X},\mathbf{m})$ is defined as class γ 's GDA synthesis function for $\mathbf{X}$ and $\mathbf{Y}$ to obtain their related feature matrixes $\mathbf{A}_{1,\gamma}^{AIB}$ and $\mathbf{Z}_{1,\gamma}^{AIB}$ by individual AIB. Obviously,

$$\mathbf{Z}_{1,\gamma}^{AIB}=\mathbf{Z}_\xi^{PIB}\quad \text{s.t. } \gamma=\xi\quad(\xi=1,2,\cdots,g).\qquad(26)$$

As aforementioned in Section 2.2, the reason that the FTs can be used for template match is the DI contained in them, but different kinds of FTs may contain different types of DI, so they may have different recognition performances. Compared with PIB, the DI extraction area of individual AIB is a bit limitary due to the personal biases, so some useful DI may be lost. Moreover, some additional redundancy information enters into the FTs of individual AIB, which directly depresses the recognition efficiency.

Let's consider the DI performances of PGA and individual AIB in the measured experiment. As shown in Fig. 2, in order to compare the DI contents, the feature distributions are projected onto the four planes with the same scale. From Fig. 2 (a, b), we can find that, the distance between the distribution centers of An-26 and Jiang by PGA, and the distance between the distribution centers of An-26 and Yark-42 by PGA, respectively, are shorter than the related distances by AIB, which indicates that the DI content in PGA is smaller than that in individual AIB. As shown in Fig. 2 (a), no matter from horizontal or vertical direction, the FT distribution of the three airplanes can be statistically discriminated due to the A-DI in them. While in Fig. 2 (b), from the vertical direction, although the FT distributions of Yark-42 and An-26 can be easily discriminated, but it's very difficult to discriminate both of them from Jiang, so the practical B-DI contained in them is obvious. Moreover, com-pared with PGA for passive recognition, individual AIB is designed for active recognition. Although a single class can estimate which class a test HRRP belongs to in some sense, she prefers to judge whether it belongs to her own class or not. Showing in Fig. 2 (c, d) is the projections of test samples obtained by PGA and individual AIB respectively, from which the performance differences between PGA and individual AIB are apparent.

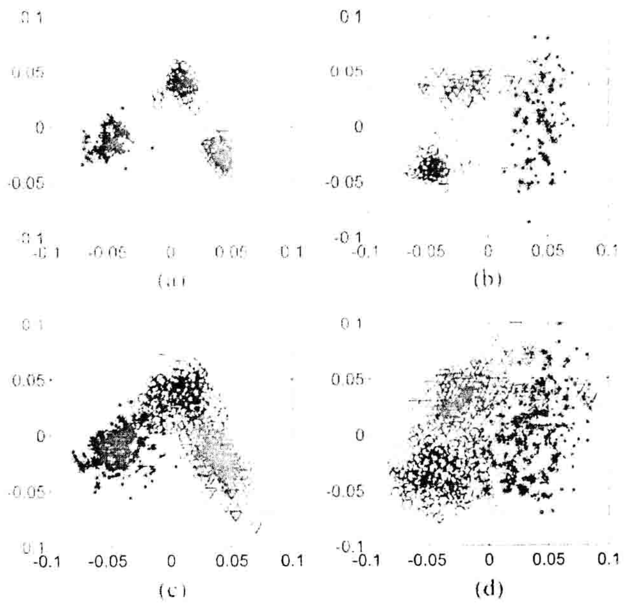

Fig. 2: Feature distributions from different standpoints in the measured experiment. (a) Distributions of 300 FTs by PGA from a general viewpoint. (b) Distributions of 300 FTs by AIB from An-26's standpoint. (c) Distributions of 900 test samples in PGA's FES from a general viewpoint. (d) Distributions of 900 test samples in AIB's FES from An-26's standpoint. ('o': An-26, '*': Jiang, '▽': Yark-42)

Since individual AIB has many native shortcomings, in order to obtain more B-DI and achieve a general performance, it is necessary to synthesize the

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the FT matrixes $\mathbf{A}_{1,\gamma}^{\mathrm{AIB}}$ by

$$\begin{cases} \begin{cases} \mathbf{A}^{\mathrm{AIB}} = \left[\mathbf{A}_{1,1}^{\mathrm{AIB}} \quad \mathbf{A}_{1,2}^{\mathrm{AIB}} \quad \cdots \quad \mathbf{A}_{1,g}^{\mathrm{AIB}} \right] \\ \mathbf{Z}^{\mathrm{AIB}} = \left[\mathbf{Z}_{1,1}^{\mathrm{AIB}} \quad \mathbf{Z}_{1,2}^{\mathrm{AIB}} \quad \cdots \quad \mathbf{Z}_{1,g}^{\mathrm{AIB}} \right] \end{cases}, \\ \left\{ \mathbf{A}^{\mathrm{AIB}}, \mathbf{Z}^{\mathrm{AIB}} \right\} \triangleq \mathbb{S}^{\mathrm{AIB}}(\mathbf{Y},\mathbf{X},\mathbf{m}) \end{cases} \qquad (27)$$

where $\mathbb{S}^{\mathrm{AIB}}(\mathbf{Y},\mathbf{X},\mathbf{m})$ is defined as the GDA synthesis function of global AIB from the standpoints of all classes, which is used for $\mathbf{X}$ and $\mathbf{Y}$ to obtain their feature matrixes $\mathbf{A}^{\mathrm{AIB}}$ and $\mathbf{Z}^{\mathrm{AIB}}$ respectively. Note that $\mathbf{A}^{\mathrm{AIB}}$ is a $(g-1)\times gM$ matrix while $\mathbf{A}^{\mathrm{PIB}}$ is a $(g-1)\times M$ matrix. Obviously, $\mathbf{Z}^{\mathrm{AIB}}$ is equal to $\mathbf{Z}^{\mathrm{PIB}}$. The total calculation process to obtain $\left\{\mathbf{A}^{\mathrm{AIB}},\mathbf{Z}^{\mathrm{AIB}}\right\}$ is defined as AIB-GDA in this paper.

4 Recognition and Analysis

Once we obtain the FTs contained the appointed DI components, we can use them for the upcoming recognition. As the simplest and the most attractive pattern classification criterions, 1-NN rule is usually used for template matching and image classifying [33], [34]. Now we apply 1-NN rule as follows.

4.1 Passive Recognition

The thought of passive recognition is widely spread in our living. It is reasonable for a person to select the most significant FTs which not only can be used to discriminate a class from all the others, but also doesn't take sides with any class. Note that the recognized classes don't take part in recognition, and the person who discriminates them seems "out of the collectivity", so we defined it as passive recognition. There are two DI extraction models for passive recognition, i.e., PGA and PIB.

Given a test HRRP $\mathbf{e}$, we can obtain the FT matrixes $\left\{\mathbf{A}_{\xi}^{\mathrm{PGA}} \middle| \mathbf{a}_{\xi,j}^{\mathrm{PGA}}, j=1,2,\cdots,m_{\xi}\right\}$ and its feature vector $\mathbf{s}_{\mathbf{e}}^{\mathrm{PGA}}$ by (20). Then we apply 1-NN rule to estimate $\mathbf{e}$ by

$$\begin{cases} d_{\mathbf{e},\xi}^{\mathrm{PGA}} = \min\limits_{j=1,2,\cdots,m_{\xi}} \left\| \mathbf{s}_{\mathbf{e}}^{\mathrm{PGA}} - \mathbf{a}_{\mathbf{e},\xi,j}^{\mathrm{PGA}} \right\| \\ \theta_{\mathbf{e}}^{\mathrm{PGA}} = \arg \min\limits_{i=1,2,\cdots,g} d_{\mathbf{e},i}^{\mathrm{PGA}} \end{cases} \quad (\xi=1,2,\cdots,g), \qquad (28)$$

where $d_{\mathbf{e},\xi}^{\mathrm{PGA}}$ denotes the Nearest Euclidean Distance (NED) between $\mathbf{e}$ and class ξ, and $\theta_{\mathbf{e}}^{\mathrm{PGA}}$ indicates that $\mathbf{e}$ belongs to class $\theta_{\mathbf{e}}^{\mathrm{PGA}}$ by PGA.

Also $\mathbf{e}$'s feature matrix $\left\{\mathbf{S}_{\mathbf{e}}^{\mathrm{PIB}} \middle| \mathbf{s}_{\mathbf{e},\gamma}^{\mathrm{PIB}}\right\}$ and the FT matrixes $\left\{\mathbf{A}_{\gamma}^{\mathrm{PIB}} \middle| \mathbf{a}_{\gamma,j}^{\mathrm{PIB}}, j=1,2,\cdots,m_{\gamma}\right\}$ can be obtained by (24). Then we apply 1-NN rule to estimate $\mathbf{e}$ by

$$\begin{cases} d_{\mathbf{e},\gamma}^{\mathrm{PIB}} = \min\limits_{j=1,2,\cdots,m_{\xi}} \left\| \mathbf{s}_{\mathbf{e},\gamma}^{\mathrm{PIB}} - \mathbf{a}_{\mathbf{e},\gamma,j}^{\mathrm{PIB}} \right\| \\ \theta_{\mathbf{e}}^{\mathrm{PIB}} = \arg \min\limits_{i=1,2,\cdots,g} d_{\mathbf{e},i}^{\mathrm{PIB}} \end{cases} \quad (\gamma=1,2,\cdots,g), \qquad (29)$$

where $d_{\mathbf{e},\gamma}^{\mathrm{PIB}}$ denotes the NED between $\mathbf{e}$ and class γ, and $\theta_{\mathbf{e}}^{\mathrm{PIB}}$ indicates that $\mathbf{e}$ belongs to class $\theta_{\mathbf{e}}^{\mathrm{PIB}}$.

4.2 Active Recognition

Not only can the test HRRP $\mathbf{e}$ be used for passive recognition, but also for active recognition. From class γ's standpoint, $\mathbf{e}$'s feature vector $\mathbf{s}_{\mathbf{e},\gamma}^{\mathrm{AIB}}$ and the FT matrixes $\left\{\mathbf{A}_{1,\xi,\gamma}^{\mathrm{AIB}} \middle| \mathbf{a}_{1,\xi,\gamma,j}^{\mathrm{AIB}}, j=1,2,\cdots,m_{\xi}\right\}$ can be obtained by (25). Then the recognition result is given by

$$\begin{cases} d_{\mathbf{e},\xi,\gamma}^{\mathrm{AIB}} = \min\limits_{j=1,2,\cdots,m_{\xi}} \left\| \mathbf{s}_{\mathbf{e},\gamma}^{\mathrm{AIB}} - \mathbf{a}_{1,\xi,\gamma,j}^{\mathrm{AIB}} \right\| \\ \theta_{1,\mathbf{e},\gamma}^{\mathrm{AIB}} = \arg \min\limits_{i=1,2,\cdots,g} d_{\mathbf{e},i,\gamma}^{\mathrm{AIB}} \end{cases} \quad (\xi,\gamma=1,2,\cdots,g), \qquad (30)$$

where $d_{\mathbf{e},\xi,\gamma}^{\mathrm{AIB}}$ denotes the NED between $\mathbf{e}$ and class ξ, and $\theta_{1,\mathbf{e},\gamma}^{\mathrm{AIB}}$ indicates that $\mathbf{e}$ belongs to class $\theta_{\mathbf{e},\gamma}^{\mathrm{AIB}}$ from the standpoint of class γ by individual AIB.

In accordance with the front analysis, it is impossible for $\mathbf{A}_{1,\xi,\gamma}^{\mathrm{AIB}}$ to contain the full appointed DI $G_{\mathrm{B},\xi,\gamma}$, besides which some redundancy information exists in $\mathbf{A}_{1,\xi,\gamma}^{\mathrm{AIB}}$. But in some sense, the practical DI $\Theta_{\mathrm{B},\xi,\gamma}^{\mathrm{AIB}}$ in $\mathbf{A}_{1,\xi,\gamma}^{\mathrm{AIB}}$, can be considered as the reflection of $G_{\mathrm{B},\xi,\gamma}$, and accordingly, the NED $d_{\mathbf{e},\xi,\gamma}^{\mathrm{AIB}}$ can be considered as the comparison result of $\Theta_{\mathrm{B},\xi,\gamma}^{\mathrm{AIB}}$ between $\mathbf{e}$ and class ξ. According to Section 2.2, since one class' B-DI obtained from her own standpoint is equivalent to the union obtained from the standpoints of all the other individuals, in order to obtain an equitable result, we synthesize the NEDs from the standpoints of all classes by

$$\begin{cases} d_{\mathbf{e},\xi}^{\mathrm{AIB}} = d_{\mathbf{e},\xi,\xi}^{\mathrm{AIB}} + \dfrac{1}{g-1} \sum\limits_{\gamma\in D(\xi,g)} d_{\mathbf{e},\xi,\gamma}^{\mathrm{AIB}} \\ \theta_{\mathbf{e}}^{\mathrm{AIB}} = \arg \min\limits_{i=1,2,\cdots,g} d_{\mathbf{e},i}^{\mathrm{AIB}} \end{cases} \quad (\xi=1,2,\cdots,g), \qquad (31)$$

where $d_{\mathbf{e},\xi}^{\mathrm{AIB}}$ denotes the NED between $\mathbf{e}$ and class ξ from a global standpoint, and $\theta_{\mathbf{e}}^{\mathrm{AIB}}$ denotes that $\mathbf{e}$ belongs to class $\theta_{\mathbf{e}}^{\mathrm{AIB}}$ by global AIB. Obviously,

$$d_{\mathbf{e},\xi,\gamma}^{\mathrm{AIB}} = d_{\mathbf{e},\xi}^{\mathrm{PIB}} \quad \text{s.t.}\ \gamma=\xi \quad (\xi=1,2,\cdots,g), \qquad (32)$$

so AIB-GDA can obtain more B-DI than PIB-GDA

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