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RADAR HRRP TARGET RECOGNITION USING MULTI-KFD-BASED LDA ALGORITHM

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Abstract—Linear double-layered feature extraction (DFE) technique has recently appeared in radar automatic target recognition (RATR). This paper develops this technique to a nonlinear field via parallelizing a series of kernel Fisher discriminant (KFD) units, and proposes a novel kernel-based DFE algorithm, namely, multi-KFD-based linear discriminant analysis (MKFD-LDA). In the proposed method, a multi-KFD (MKFD) parallel algorithm is constructed for feature extraction, and then the projection features on the MKFD subspace are further processed by LDA. Experimental results on radar HRRP databases indicate that, compared with some classical kernel-based methods, the proposed MKFD-LDA not only performs better and more harmonious recognition, but also keeps higher robustness to kernel parameters, lower training computational cost, and competitive noise immunity.

1. INTRODUCTION

Double-layered feature extraction (DFE) technique via connecting two linear methods in series has appeared in radar target recognition over the last few years. With respect to these linear DFE methods, principal components analysis (PCA) was usually employed in the first stage to process the original features for noise and dimension reduction, and then the compressed projection features on the PCA subspace were further processed by other linear methods, such as independent component analysis (ICA) [1, 2], linear discriminant analysis (LDA) [3, 4], pseudo spectrum multiple signal classification (MUSIC) [5], for more reliable or better discrimination performance. In fact, PCA can be applied not only in the first stage, but also in the second stage. For example, *Turhan-Sayan* used the

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Wigner transformation to characterize the target's scattered energy distribution over a selected late-time segment of the joint time-frequency plane in the first stage, and then the processed features are fused by PCA to obtain a single characteristic feature vector that can effectively represent the target of concern over a broad range of aspect angles [6].

Although successful in many applications, these DFE methods cannot perform well for nonlinear problems due to their linear nature. To overcome this weakness, kernel-based methods have been recently applied in pattern recognition [7–14]. *Mika* et al. formulated kernel Fisher discriminant (KFD) for two-class problems [9], while *Baudat* and *Anouar* developed generalized discriminant analysis (GDA) for multi-class cases [10]. As the direct extension of KFD, GDA usually outperforms many other nonlinear methods in radar high resolution range profile (HRRP) target recognition [12, 13], but it deals with multi-class problems by extending the kernel scatter matrices, which may result in the computation and storage problem for large scale dataset.

Motivated by the linear DFE technique, this paper develops it to a nonlinear field, and proposes another KFD extension for multi-class cases, in which the first feature extraction sub-process is implemented by a multi-KFD (MKFD) parallel algorithm, and then the projection features on the MKFD subspace are further processed by LDA. The total process is defined as MKFD-based LDA (MKFD-LDA) algorithm. The efficiency of the proposed method is demonstrated by experiments on the measured and simulated radar HRRP databases.

2. NEW FORMULATIONS OF GDA AND KFD

Throughout this paper, consider a set of M training samples $\{\mathbf{X}|\mathbf{x}_i,\, i = 1,\, 2,\, \ldots,\, M\}$ defined on a n-dimensional space $\mathbb{R}^n$, containing g classes with each class consisting of m_ξ training samples ($\xi = 1,\, 2,\, \ldots, g$). Let $\{\mathbf{X}_\xi|\mathbf{x}_{\xi,j},\ j = 1,\, 2,\, \ldots, m_\xi\}$ denote class ξ's training sample subset, thus we have $M = \sum_{\kappa=1}^{g} m_\kappa$ and $\mathbf{X} = [\mathbf{X}_1,\, \mathbf{X}_2,\, \ldots,\, \mathbf{X}_g]$.

Let $\Phi : \mathbf{x} \in \mathbb{R}^n \rightarrow \Phi(\mathbf{x}) \in \mathbb{F}$ be a nonlinear mapping from the input space $\mathbb{R}^n$ to an implicit high-dimensional feature space $\mathbb{F}$. Given two random subsets $\mathbf{X}_w$ and $\mathbf{X}_v$ ($w, v = 1,\, 2,\, \ldots,\, g$), without knowing Φ explicitly, we can obtain the kernel matrix $\mathbf{K}_{w,v}$ on $\mathbb{F}$ by applying a Mercer kernel $\mathrm{k}(\mathbf{x}_{w,i}, \mathbf{x}_{v,j}) = \langle \Phi(\mathbf{x}_{w,i}),\, \Phi(\mathbf{x}_{v,j})\rangle$ as that:

$$\mathbf{K}_{w,v} = \left(\mathrm{k}(\mathbf{x}_{w,i}, \mathbf{x}_{v,j})\right)_{i=1,2,\ldots,m_w;\ j=1,2,\ldots,m_v} \triangleq \mathbf{k}(\mathbf{X}_w, \mathbf{X}_v), \qquad (1)$$

where $\mathbf{k}\,(\mathbf{X}_w,\, \mathbf{X}_v)$ is defined as the kernel matrix function, and $\mathbf{K}_{w,v}$ is a $m_w \times m_v$ kernel matrix, here $w, v = 1,\, 2,\, \ldots,\, g$.

Given the kernel symmetric matrix (KSM) $\mathbf{Q} = \mathbf{k}(\mathbf{X}, \mathbf{X})$ and the block diagonal matrix $\mathbf{W} = \mathrm{diag}(\mathbf{1}_{m_1}, \mathbf{1}_{m_2}, \ldots, \mathbf{1}_{m_g})$, here the mean value matrix $\mathbf{1}_\eta$ $(\eta = m_1, m_2, \ldots, m_g)$ is a $\eta \times \eta$ matrix with elements all equal to $1/\eta$, $\mathbf{Q}$ and $\mathbf{W}$ are all $M \times M$ matrices. Then the kernel scatter matrices can be defined by

$$\mathbf{K}_\mathrm{b} = \mathbf{QWQ}, \qquad \mathbf{K}_\mathrm{t} = \mathbf{QQ}, \qquad \mathbf{K}_\mathrm{w} = \mathbf{K}_\mathrm{t} - \mathbf{K}_\mathrm{b}, \tag{2}$$

where $\mathbf{K}_\mathrm{b}$, $\mathbf{K}_\mathrm{w}$ and $\mathbf{K}_\mathrm{t}$, respectively, denote the between-class, within-class and total kernel scatter matrices, and they are all $M \times M$ symmetric matrices.

As explored in [10], the essence of GDA is to find an optimal feature extraction subspace (FES) by maximizing the between-class distance and minimizing the within-class distance. Under a variant of Fisher criterion, it aims to solve an optimization problem:

$$J(\mathbf{u}_\mathrm{opt}) = \arg\max_{\mathbf{u}} \frac{\mathbf{u}^\mathrm{T}\mathbf{K}_\mathrm{b}\mathbf{u}}{\mathbf{u}^\mathrm{T}\mathbf{K}_\mathrm{t}\mathbf{u}} \Leftrightarrow \arg\max_{\mathbf{u}} \frac{\mathbf{u}^\mathrm{T}\mathbf{K}_\mathrm{b}\mathbf{u}}{\mathbf{u}^\mathrm{T}\mathbf{K}_\mathrm{w}\mathbf{u}}. \tag{3}$$

Then according to the solution offered in [10], we can obtain a series of optimal coefficient vectors $\mathbf{u}_i$ $(i = 1, 2, \ldots, \tau;\ \tau \leq g - 1)$ from (3), which can be arranged as the FES of GDA by

$$\mathbf{U} = [\,\mathbf{u}_1 \quad \mathbf{u}_2 \quad \ldots \quad \mathbf{u}_\tau\,] \triangleq \mathrm{F}_\mathrm{GDA}(\mathbf{X},\mathbf{m}), \tag{4}$$

where $\mathrm{F}_\mathrm{GDA}(\mathbf{X}, \mathbf{m})$ is defined as the GDA function for the FES $\mathbf{U}$ $(\tau \times M)$, and the vector $\mathbf{m}$ is given by $\mathbf{m} = [\,m_1 \quad m_2 \quad \ldots \quad m_g\,]$.

As the direct extension of KFD, when GDA is applied for two-class cases, it is mathematically equivalent to KFD. Suppose that GDA is used to discriminate class γ and ξ, then only one optimal coefficient vector $\mathbf{u}_{\gamma,\xi}$ is adopted to construct the FES of KFD, that is,

$$\begin{array}{c} \mathbf{u}_{\gamma,\xi} = \mathrm{F}_\mathrm{GDA}(\mathbf{X}_{\gamma,\xi}, \mathbf{m}_{\gamma,\xi}) \triangleq \mathrm{F}_\mathrm{KFD}(\mathbf{X}_{\gamma,\xi}, \mathbf{m}_{\gamma,\xi}) \\ (\gamma, \xi = 1, 2, \ldots, g;\ \gamma \neq \xi) \end{array}, \tag{5}$$

where $\mathrm{F}_\mathrm{KFD}(\mathbf{X}_{\gamma,\xi}, \mathbf{m}_{\gamma,\xi})$ is defined as the KFD function for the FES $\mathbf{u}_{\gamma,\xi}$, the training sample subset $\mathbf{X}_{\gamma,\xi}$ and the vector $\mathbf{m}_{\gamma,\xi}$, respectively, are given by $\mathbf{X}_{\gamma,\xi} = [\,\mathbf{X}_\gamma \quad \mathbf{X}_\xi\,]$ and $\mathbf{m}_{\gamma,\xi} = [\,m_\gamma \quad m_\xi\,]$. Obviously, $\mathbf{u}_{\gamma,\xi}$ is a $(m_\gamma + m_\xi)$-dimensional column vector.

3. MKFD-LDA ALGORITHM

As aforementioned in Section 1, the proposed MKFD-LDA realizes the DFE process via connecting MKFD and LDA in series. The analysis is detailed as follows.

3.1. Feature Extraction Process

When the traditional KFD is applied in a g-class recognition system under the so called "one-against-one" strategy [7, 8], it needs C_g^2 units to cover the whole system, here $C_g^\xi = \prod_{i=1}^{g} i/((\prod_{j=1}^{g-\xi} j)(\prod_{k=1}^{\xi} k))$, $(\xi = 1, 2, \ldots, g)$. The total parallel process of these $\frac{g(g-1)}{2}$ KFD units is defined as MKFD in this paper. According to (1, 5), the projection subset $\mathbf{y}_{\gamma,\xi}$ of each KFD unit is obtained by

$$\mathbf{y}_{\gamma,\xi} = \mathbf{k}(\mathbf{X}, \mathbf{X}_{\gamma,\xi})\mathbf{u}_{\gamma,\xi} \quad (\gamma, \xi = 1, 2, \ldots, g; \gamma \neq \xi), \tag{6}$$

and then the first projection features are constructed in series by

$$\mathbf{Y} = [\mathbf{y}_{1,2} \quad \mathbf{y}_{1,3} \quad \cdots \quad \mathbf{y}_{1,g} \quad \mathbf{y}_{2,3} \quad \mathbf{y}_{2,4} \quad \cdots \quad \mathbf{y}_{g-1,g}], \tag{7}$$

where the $M \times (g(g-1)/2)$ matrix $\mathbf{Y}$ is the first projection feature subset, in which each row vector denotes the projection feature of a related training sample.

Let's consider the optimal coefficient vector $\mathbf{u}_{\gamma,\xi}$ obtained by (5), which can be divided into two sub-vectors, that is,

$$\mathbf{u}_{\gamma,\xi} = \begin{bmatrix} \mathbf{u}_{\gamma,\xi}^{(\gamma)} \\ \mathbf{u}_{\gamma,\xi}^{(\xi)} \end{bmatrix}, \qquad (\gamma, \xi = 1, 2, \ldots, g;\ \gamma \neq \xi)\ , \tag{8}$$

where $\mathbf{u}_{\gamma,\xi}^{(\gamma)}$ and $\mathbf{u}_{\gamma,\xi}^{(\xi)}$ denote the coefficient sub-vectors with m_γ and m_ξ elements, respectively. Then we construct a M-dimensional column vector $\mathbf{v}_{\gamma,\xi}$ via arranging $\mathbf{u}_{\gamma,\xi}^{(\gamma)}$, $\mathbf{u}_{\gamma,\xi}^{(\xi)}$ and zeros vectors by

$$\mathbf{v}_{\gamma,\xi} = \begin{bmatrix} \mathbf{v}_{\gamma,\xi}^{(1)} \\ \mathbf{v}_{\gamma,\xi}^{(2)} \\ \vdots \\ \mathbf{v}_{\gamma,\xi}^{(g)} \end{bmatrix} \quad \begin{array}{c} \text{s.t.}\ \mathbf{v}_{\gamma,\xi}^{(\kappa)} = \begin{cases} \mathbf{0}_{m_\kappa} & \kappa \notin \{\gamma, \xi\} \\ \mathbf{u}_{\gamma,\xi}^{(\kappa)} & \kappa \in \{\gamma, \xi\} \end{cases} \\ (\kappa,\ \gamma,\ \xi = 1, 2, \ldots, g;\ \gamma \neq \xi) \end{array}, \tag{9}$$

where $\mathbf{0}_\eta\,(\eta = m_1,\, m_2,\, \ldots,\, m_g)$ is defined as a η-dimensional column zeros vector with elements all equal to 0.

According to (6)–(9), the projection subsets $\mathbf{y}_{\gamma,\xi}$ are computed by

$$\begin{array}{c} \mathbf{y}_{\gamma,\xi} = \mathbf{k}(\mathbf{X}, \mathbf{X}_{\gamma,\xi})\mathbf{u}_{\gamma,\xi} = \mathbf{k}(\mathbf{X}, \mathbf{X})\mathbf{v}_{\gamma,\xi} \\ (\gamma, \xi = 1, 2, \ldots, g;\ \gamma \neq \xi) \end{array}, \tag{10}$$

and hence the first projection feature matrix $\mathbf{Y}$ is obtained by

$$\begin{cases} \mathbf{Y} = \mathbf{k}(\mathbf{X}, \mathbf{X})\mathbf{U}_{\mathrm{M}} \\ \mathbf{U}_{\mathrm{M}} \triangleq [\mathbf{v}_{1,2} \quad \mathbf{v}_{1,3} \quad \cdots \quad \mathbf{v}_{1,g} \quad \mathbf{v}_{2,3} \quad \mathbf{v}_{2,4} \quad \cdots \quad \mathbf{v}_{g-1,g}] \end{cases}, \tag{11}$$

where the $M \times (g(g-1)/2)$ matrix $\mathbf{U}_{\mathrm{M}}$ denotes the FES of MKFD.

After achieving the first projection feature subset $\mathbf{Y}$ on the FES of MKFD, we can directly discriminate it by the traditional LDA without any preprocessing [3, 4], and thereby obtain the FES of LDA, on which the second projection feature subset $\mathbf{Z}$ can be calculated by

$$\begin{cases} \mathbf{Z} = \mathbf{Y}\mathbf{U}_{\mathrm{L}} = \mathbf{k}(\mathbf{X},\mathbf{X})\mathbf{U}_{\mathrm{M}}\mathbf{U}_{\mathrm{L}} = \mathbf{k}(\mathbf{X},\mathbf{X})\mathbf{U}_{\mathrm{ML}} \\ \mathbf{U}_{\mathrm{ML}} \triangleq \mathbf{U}_{\mathrm{M}}\mathbf{U}_{\mathrm{L}} \end{cases}, \tag{12}$$

where the $\frac{g(g-1)}{2} \times (g-1)$ matrix $\mathbf{U}_{\mathrm{L}}$ denotes the FES of LDA, and the $M \times (g-1)$ matrix $\mathbf{U}_{\mathrm{ML}}$ denotes the FES of MKFD-LDA. Obviously, $\mathbf{U}_{\mathrm{ML}}$ can be considered as the series connection of $\mathbf{U}_{\mathrm{M}}$ and $\mathbf{U}_{\mathrm{L}}$.

3.2. Operation Efficiency Analysis Compared with GDA

Different from several classical kernel-based algorithms, such as GDA, by extending the kernel scatter matrices for multi-class cases, the proposed MKFD-LDA algorithm implements another extensional style of KFD via using many traditional KFD units "one-against-one" for multi-class discrimination. As two different extensional styles of KFD, although MKFD-LDA and GDA have the same test time-complexity (TC), but their training TCs are somewhat different. Due to the fact that the training sample number M is usually far greater than the class number g in practical application, the training TC of the LDA sub-process can be overlooked compared with that of MKFD in MKFD-LDA. Then compared with GDA, MKFD-LDA partially reduces the training TC via dividing the large KSM $\mathbf{k}\,(\mathbf{X},\, \mathbf{X})$ into a series of small ones $\mathbf{k}\,(\mathbf{X}_{\gamma,\,\xi},\, \mathbf{X}_{\gamma,\,\xi})$, here $\gamma, \xi = 1, 2, \ldots, g$ and $\gamma \neq \xi$. On condition that all classes have the same training sample number, the training TCs of MKFD-LDA and GDA can be approximately given by $O\,(nM^2 + 4\frac{\mathrm{g}-1}{g^2}M^3)$ and $O\,(nM^2 + M^3)$, respectively [10, 12, 14]. Obviously, with the class number g increasing, the training TC ratio of MKFD-LDA to GDA is decreasing accordingly.

Also we can find that the space-complexity of MKFD-LDA is only about $4/g^2$ times of GDA's. Even though the computation cost in the training phase can be ignored for an off-line training system, the EMS memory is still a gordian knot in radar HRRP-based recognition due to the huge storage requirement and computation burden which may lead to the program error "out of memory".

Furthermore, MKFD-LDA is naturally convenient for distributed computing and dynamic database building, thereby further depressing the processing time. When a new class is put into this g-class system, the large KSM $\mathbf{k}\,(\mathbf{X},\, \mathbf{X})$ in GDA changes accordingly, so its pseudo inverse should be recomputed for new FES. But for MKFD-LDA, it only needs to add other g KFD units while the previous ones are still effective. Although the first projection feature subset $\mathbf{Y}$ changes partly, but the dimension of the training database has been greatly reduced, so it can be rapidly processed by LDA in the next phase.

Based on the analysis above, MKFD-LDA is theoretically superior to GDA in terms of operation efficiency.

4. EXPERIMENTS

An original HRRP represents the projection of the complex returned echoes from the target scattering centers onto the radar line-of-sight (LOS), so it contains abundant target information, such as target size, scatterer distribution, etc., and can be applied for target recognition [1–4, 12–19]. In this paper, several experiments are performed on the simulated and measured radar HRRP database, respectively. Before experiments, each original HRRP is aligned by cross-correlation and preprocessed by energy normalization [15, 16]. In addition to MKFD-LDA, three discriminant mehthods, i.e., GDA, kernel direct discriminant analysis (KDDA) [11] and LDA, are also adopted for a performance comparison. Note that in KDDA the original kernel between-class scatter matrix is adopt instead of the compressed one. For MKFD-LDA, GDA and KDDA, the typical Gaussian kernel $\mathrm{k}(\mathbf{x}, \mathbf{y}) = \exp(-||\mathbf{x} - \mathbf{y}||^2/2\sigma^2)$ is employed with σ set to 0.8 except additional description. Finally, the nearest neighbor classifier is implemented for classification, and the Euclidean metric is used as the distance measure [14].

All the implementations are based on MATLAB 7.1 and performed on a 2.66-GHz Pentium(R)-4 machine which has 1-GB EMS memory and runs Windows XP operation system.

4.1. Experiment on Operation Efficiency

To demonstrate the operation efficiency of MKFD-LDA, we simulate the radar backscattering data of seven airplanes by a software [14, 15, 20]. The airplane simulated parameters are offered in Table 1, and the radar simulated parameters are mainly provided with center frequency 5520 MHz, bandwidth 400 MHz, sampling frequency 800 MHz and pulse repetition frequency 1000 Hz. As these airplanes are all symmetrical in horizontal, we only simulate HRRPs with azimuthal angle ranging from 0° to 180° at interval 0.5°, and the sampling length is set to 400. All the simulated HRRP data is used in the training phase to evaluate the operation efficiency of MKFD-LDA, GDA, KDDA and LDA. Their average training runtimes in the C_7^k k-class subsystems are list in Table 2, here $k = 2, 3, \ldots, 7$. Note that in the

Table 1. The simulated parameters of seven airplanes.

airplanes	B-52	B-1B	Tu-16	F-15	Tornado	Mig-21	An-26
length (m)	49.50	44.80	33.80	19.43	16.72	15.76	23.80
width (m)	56.40	23.80	33.00	13.05	13.91	7.15	29.21
scale	1 : 1	1 : 1	1 : 1	1 : 1	1 : 1	1 : 1	1 : 1

Table 2. Average training runtimes (s) in the simulated experiment.

class number	2	3	4	5	6	7
MKFD-LDA	5.8660	16.6083	32.7359	54.3036	81.2987	113.8206
GDA	5.7404	16.6719	36.1482	67.3263	111.7887	173.0470
KDDA	5.1669	15.3703	33.9777	64.5225	108.8133	171.3137
LDA	0.2616	0.2718	0.2807	0.2897	0.2995	0.3161

simulated experiments, each subsystem repeats experiments 20 times to obtain the average training time-consuming.

Firstly, let's consider the three nonlinear methods. From Table 2 we can see that, in terms of training runtime, the proposed MKFD-LDA is obviously lower than GDA in most cases while GDA and KDDA are roughly similar. With the class number increasing, although their training runtimes are all increasing rapidly, but the difference between MKFD-LDA and GDA becomes more and more apparent. When the class number is 7, the training runtime of MKFD-LDA decreases about 34.23%, compared with that of GDA.

Secondly, let's consider the linear method. It can be found from Table 2 that, compared with the three nonlinear methods, LDA keeps a far lower training runtime. Note that the sample dimension is no more than $\frac{7\times(7-1)}{2} = 21$ in the LDA sub-process of MKFD-LDA while 200 in LDA, so the training time-consuming of the LDA sub-process can be overlooked, compared with that of MKFD in MKFD-LDA.

4.2. Experiments on Recognition Performance

The practical HRRP data used to evaluate the recognition performance was measured from three flying airplanes [12–16], including the 1st, 2nd, 4th and 7th segments of An-16, the 1st, 2nd, 4th and 7th segments of Jiang (Cessna Citation S/II), and the 1st, 2nd, 4th and 5th segments of Yak-42. The projections of target flying trajectories onto the ground plane are shown in Fig. 1, from which the aspect angle of an airplane can be estimated according to its relative position to radar. Each

Table 3. Correct recognition rates (%) in the measured experiment.

methods	An-16	Jiang	Yak-42	average	standard deviation
MKFD-LDA	89.89	93.11	94.44	92.48	2.34
GDA	85.78	92.44	92.22	90.15	3.78
KDDA	84.11	90.67	90.67	88.48	3.79
LDA	77.89	79.56	67.56	75.00	6.50

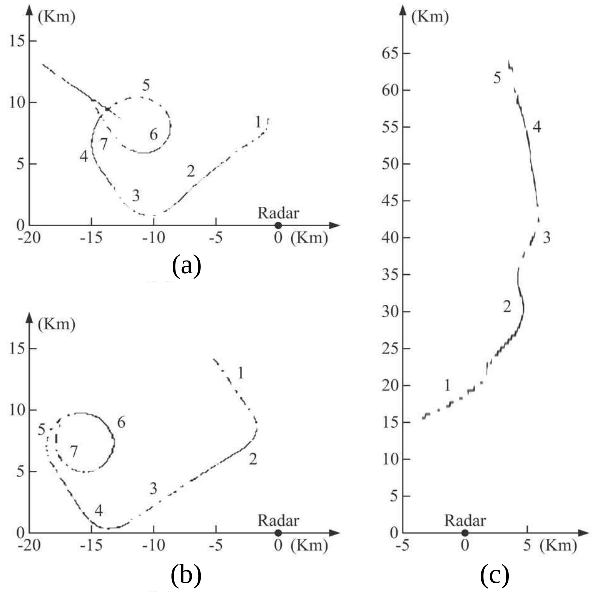

Figure 1. The projections of target trajectories onto the ground plane. (a) An-26. (b) Jiang. (c) Yak-42.

target provides 1000 profiles, of which the training samples are selected at interval 10 profiles along the flying trajectory and the rest ones for test.

The recognition rates of each target are listed in Table 3, which indicate that MKFD-LDA not only achieves the best results on each airplane and average, but also performs the most harmonious recognition in terms of standard deviation. As compared with LDA, the recognition superiority of the three nonlinear methods, especially MKFD-LDA, is very apparent.

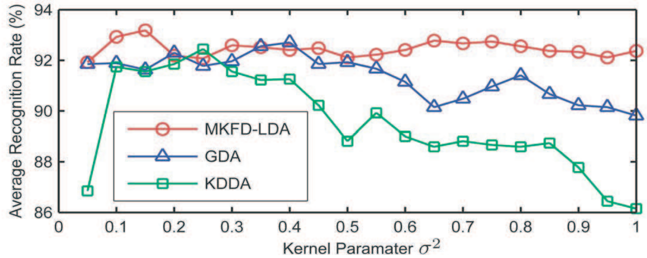

Figure 2. Variation of the recognition performance with σ^2.

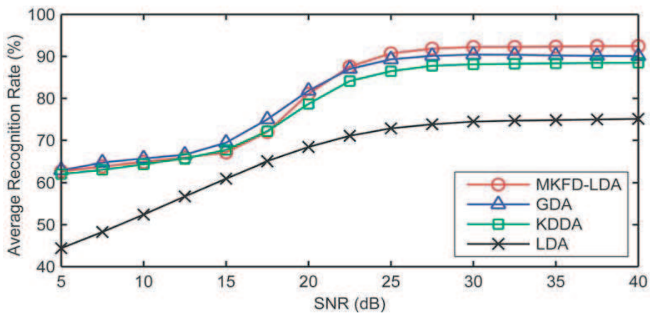

Figure 3. Variation of the recognition performance with SNR.

To further compare the performance of MKFD-LDA, GDA and KDDA, sensitivity analysis is also performed with respect to the kernel parameter σ^2. Fig. 2 depicts the averaged recognition rates of the three methods as functions of σ^2 ranging from 0.05 to 1, in which the results show that GDA and KDDA are both very sensitive to the variations of kernel parameter σ^2. In contrast, we can easily see that MKFD-LDA performs the best and is relatively stable within the whole ranges of σ^2, which is highly desirable in practical applications since it is usually not easy to determine very suitable parameter values.

Additionally, to evaluate the noise effect on these methods, a series of simulated white noises are added to the inphase and quadrature components of the original test data [16]. Each SNR level repeats 50 times to obtain the average. Fig. 3 depicts the average recognition rates versus signal-to-noise ratio (SNR), from which we can find that the three kernel-based methods have a similar stability and sensitivity to noises within the whole ranges of SNR. From a global look at their recognition performances, the three nonlinear methods are all apparently better than LDA while more sensitive to noises within SNR ranging from 15 dB to 22.5 dB. When the SNR surpasses 20 dB, the average recognition rates are labeled from high to low by MKFD-LDA, GDA, KDDA and LDA. One opinion worth pointing out is that some pretreatment methods are usually employed to denoise the original signals in practical applications [21], so we usually obtain the HRRPs with high SNR before discriminant analysis.

5. CONCLUSION

Different from several classical kernel-based methods by extending the kernel scatter matrices for multi-target discrimination, a novel MKFD-LDA algorithm is proposed in which the first feature extraction sub-process is implemented by a MKFD parallel algorithm, and then the first projection features on the FES of MKFD are further processed by LDA for the second feature extraction. In terms of operation efficiency, MKFD-LDA is superior to GDA in theory. Experimental results on the simulated and measured radar HRRP databases show that, compared with the two classical kernel-based methods, i.e., GDA and KDDA, the proposed MKFD-LDA not only performs better and more harmonious recognition, but also keeps higher robustness to kernel parameters, lower training computational cost, and competitive noise immunity.

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