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Radar HRRP Target Recognition Based on the Improved Kernel Distance Fuzzy C-Means Clustering Method

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SUMMARY To overcome the target-aspect sensitivity in radar high resolution range profile (HRRP) recognition, a novel method called Improved Kernel Distance Fuzzy C-means Clustering Method (IKDFCM) is proposed in this paper, which introduces kernel function into fuzzy c-means clustering and relaxes the constraint in the membership matrix. The new method finds the underlying geometric structure information hiding in HRRP target and uses it to overcome the HRRP target-aspect sensitivity. The relaxing of constraint in the membership matrix improves anti-noise performance and robustness of the algorithm. Finally, experiments on three kinds of ground HRRP target under different SNRs and four UCI datasets demonstrate the proposed method not only has better recognition accuracy but also more robust than the other three comparison methods.

key words: *fuzzy c-means clustering method (FCM), high-resolution range profile (HRRP), radar automatic target recognition (RATR), kernel function*

1. Introduction

The ability to detect and locate targets on a day/night, all-weather basis, over wide areas, has long made radar a key sensor in many military and civilian applications [1]. It is well recognized that the utility of the information supplied by a radar system would be hugely enhanced if targets could additionally be recognized. Compared with other wideband radar signals, such as synthetic aperture radar (SAR) images and inverse synthetic aperture radar (ISAR) images, the HRRP is easy to obtain and needs less storage space. Most of all, the HRRP provides the underlying geometry structure of the target, which is promising information for target recognition. Therefore, Radar HRRP target recognition (RATR) has received intensive attention by the RATR community in recent years [1]–[19]. Several issues should be taken into account when HRRP is used in the radar target recognition [2]. The first one is target-aspect sensitivity of HRRP, the scattering center model [3] and coherent averaging [4] have been widely studied to surmount it. The HRRP is the amplitude of the coherent summation of the complex time, which returns from the target scattering centers in each range resolution cell and the variation of target aspect will lead to different range shift for different scattering centers on the target. The scattering center model assumes that one target can be modeled as a number of scatters and a small target aspect change leads to the HRRP change violently, however, if there is no migration through resolution cell (MTRC) [3], [6], HRRP does not change much. Coherent averaging looks an averaged HRRP as a template, which gets a better signal to noise ratio (SNR) than other methods. The second one is time-shift sensitivity. A HRRP is just the radar echoes in a range window, the length of which is decided by the radar parameters, different range windows lead to different HRRPs. We can use the shift matching method [7], [8] or extract the shift invariant features [9]–[11] to solve this problem. The last one is amplitude-scale sensitivity of HRRP. The amplitude of HRRP is determined by the amplitude of target echoes, which is influenced by the radar transmitting power, target distance, atmospheric attenuation and so on. All these lead the HRRP measured in a different environment will have different result and increase the difficulty of feature extraction. Considering the three sensitivities of the radar HRRP target, how to mix the feature extraction method and classification algorithm in the field of RATR is widely studied [11]–[18].

In the existing literatures, reference [3] and [18] discussed the properties of radar HRRP, the bispectra has been well studied in [9], [10]. In order to avoid the huge computation burden in bispectra method, some dimensionality reduction methods were proposed in [6], [11], [15]. Hidden Markov model was used in radar HRRP target recognition and studied in [19]; some time-shift invariant features of radar HRRP target were proposed in [5], [7]–[11]; the statistical recognition model was studied in [12], [14], [17]; many classifiers were proposed in [13], [15], [16]. there has been little work, however, in the field of radar HRRP target based fuzzy clustering algorithm.

The fuzzy c-means clustering method (FCM) is a type of fuzzy clustering algorithm, which was proposed by Dunn in [20] and developed by Bezdek [21]. Both the analysis and experiments show that the FCM is susceptible to the noise and can't guarantee convergence to the global optimal. To solve this problem, the possibilistic clustering method (PCM) [22] and possibilistic fuzzy c-means clustering method (PFCM) [23] were proposed. Although the PCM and the PFCM have better robustness to the noise than FCM, the PCM is easy to get the overlap clustering result and the PFCM needs to initialize various parameters, both of them are sensitive to the initial value of parameters. Thankfully, the kernel function can solve the problems mentioned above perfectly [24], [25]. The introducing of kernel function into the fuzzy c-means clustering algorithm makes the algorithm

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has the capacity to find the non-convex structure in the clustering data.

In this paper, we considered the target-aspect sensitivity problem in the radar HRRP target and the shortcomings of the clustering algorithm mentioned above. Based on pre-existing algorithms, we proposed an improved algorithm for the recognition of radar HRRP target, called improved kernel distance fuzzy c-means clustering method (IKDFCM). We first introduce the kernel function into the fuzzy c-means method (FCM) algorithm. The function of the kernel function is tantamount to map the non-linear radar HRRP target data from the original low-dimensional data space to the high-dimensional feature space, and use the inner product to calculate the distance between two points in the high-dimensional feature space. The kernel function can find the steady underlying geometric structure information in the HRRP target and uses it to surmount the target-aspect sensitivity. Besides, we relax the column sum constraint of the membership matrix in FCM algorithm from one to n. This change makes the IKDFCM have the better anti-noise and robust performance. Finally, recognition experiments based on radar HRRP of three different targets and four UCI public datasets are made, the result show that the proposed method not only has the better recognition accuracy, but more robust to noise compared with the other three contrast methods. In the IKDFCM algorithm, we choose the radial basis function (RBF) as the kernel function and the Euclidean distance as the distance of two points in the high-dimensional feature space.

The rest of paper is organized as follows: In Sect. 2, we review the related work in the field of radar HRRP target recognition and the theory of FCM. In Sect. 3, the Improved Kernel Distance Fuzzy C-means Clustering Method algorithm is discussed in detail. In Sect. 4, we perform experiments on the electromagnetic simulation radar HRRP target to evaluate the effectiveness of our method. Conclusions and summary are made in Sect. 5.

2. The Related Work

2.1 The Target-Aspect Sensitivity of Radar HRRP

According to the scattering model in [4], the radar target doesn't appear as a "point target" any longer if the target is much larger than the wavelength of millimeter radar, but consists of many scatters separated in range cells along the radar line of sight (LOS). The HRRP is the amplitude of the coherent sum of the complex time returns from the scatters in each range cell as showed in Fig. 1. From the Fig. 1 we know that the slight variation of target-aspect caused scatters remove from one range cell to another and conspicuous change of the HRRP, we call this phenomenon MTRC. The limitation of target-aspect change for avoiding MTRC is given in literature [2] and [6].

$$\delta_\varphi \leq (\delta_\varphi)_{MTRC} = \frac{C}{2BL_x} \tag{1}$$

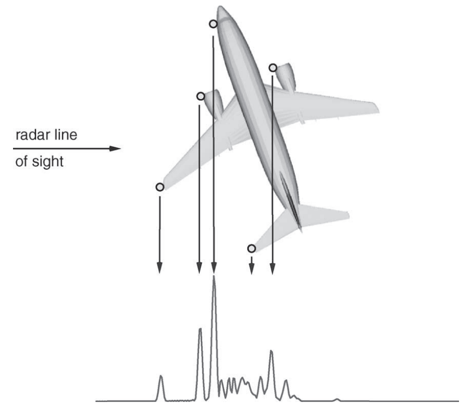

Fig. 1 HRRP of an aircraft, it shows the discriminative information on the geometry of aircraft. This figure is cited from [5].

Where B is the bandwidth of the radar signal, L_x is the maximum target size in cross range and C is the speed of light.

The HRRP of the ground target has the exact same characteristics with the aircraft target. In this paper the HRRP we used are three different ground targets. They are BMP2, T72 and BTR70. As the real targets and real radar echoes data is hard to obtain, we just set up the electromagnetic scattering model according to the geometric model of the real target and use the step frequency wave (SFW) radar to get the simulated HRRP of the target through Matlab. Optical images and corresponding HRRP of the three targets are shown in Fig. 2. The azimuth of (d), (e), (f) is 30° and the azimuth of (g), (h), (i) is 60°, compared the (d) with (g), (e) with (h) and (f) with (i) in Fig. 2, we can see the target-aspect sensitivity clearly.

2.2 Theory of the FCM Algorithm

The principle of the FCM algorithm is to minimize the objective function which based on a certain norm or clustering prototype. It's aims at pointing out what degree of the sample data is affiliated to these clusters and classifying n sample data $X = \{x_1, x_2, \ldots, x_n\} \subset R^s$ into c $(c > 1)$ categories so as to compute the clustering centroid $V = \{v_1, v_2, \ldots, v_c\} \subset R^s$ of each group, s is the dimension of the sample, n is the number of the samples, c is the number of categories. The merit function of the FCM algorithm can describe as Eq. (2).

$$Min\ J_{fcm}(U, V) = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^m d_{ij}^2 \tag{2}$$

Subject to

$$\begin{aligned} &\sum_{i=1}^{c} u_{ij} = 1,\ 1 \leq j \leq n. \\ &\sum_{j=1}^{n} u_{ij} > 0,\ 1 \leq i \leq c. \\ &u_{ij} \geq 0,\ 1 \leq i \leq c,\ 1 \leq j \leq n. \end{aligned} \tag{3}$$

Where m is called the fuzzy exponent, it has influence

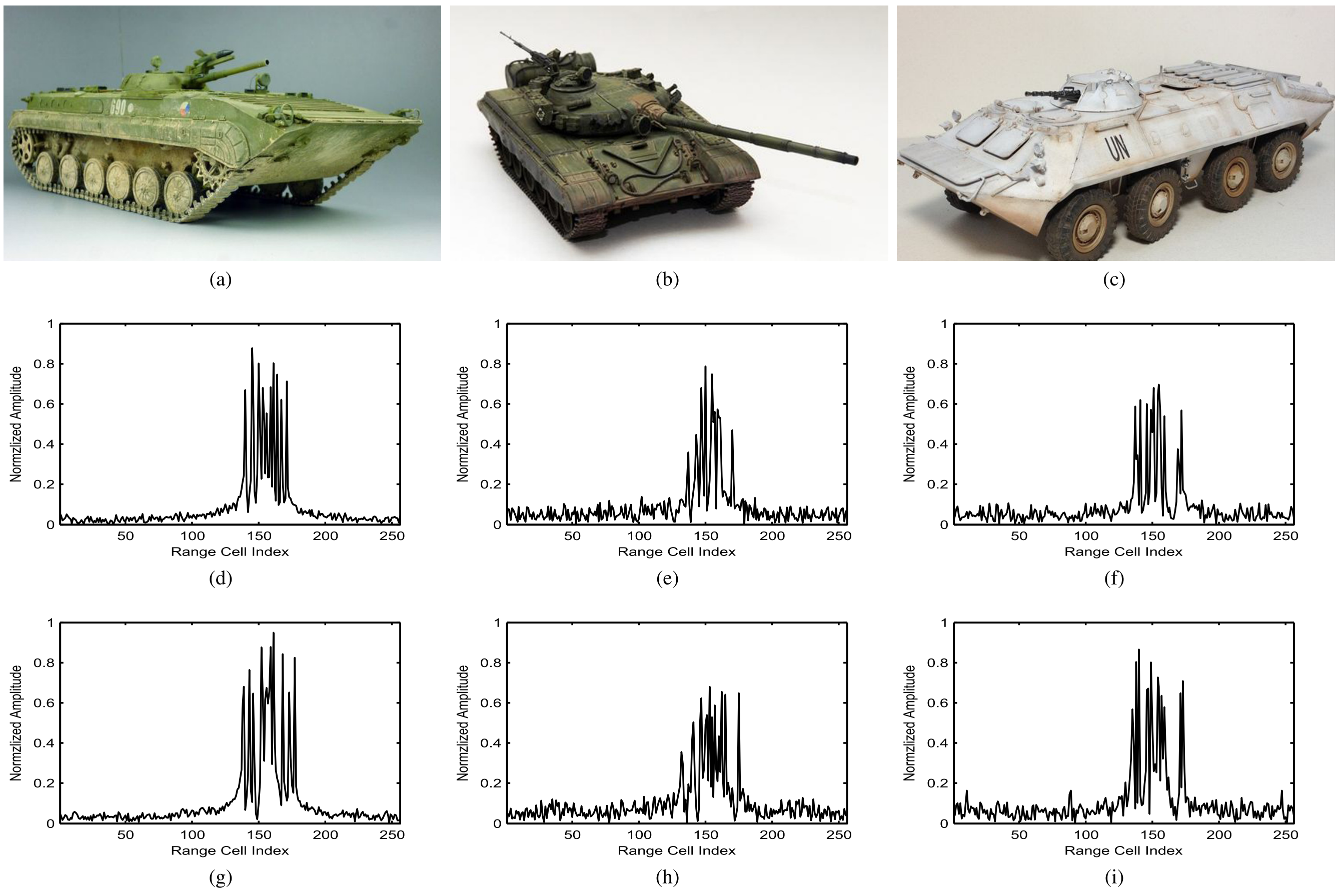

Fig. 2 The optical images [33] and the HRRP of the three targets. (a) the optical image of BMP2; (b) the optical image of BTR70; (c) the optical image of T72; (d)–(f) the HRRP of the corresponding three targets above when the azimuth is 30°; (g)–(i) the HRRP of the corresponding three targets above when the azimuth is 60°.

on the clustering performance of FCM, $U = u_{ij}$ ($i = 1, 2, \ldots, c,\ j = 1, 2, \ldots, n$) is the membership matrix, and u_{ij} represents the affiliating degree that the jth sample belongs to the jth class, $V = [v_1, v_2, \ldots, v_c]$ is the vector composed by clustering centroid. $d_{ij} = \|x_i - v_j\|$ is the Euclidean norm between x_j and v_i. The clustering centroid and the respective membership functions that solve the constrained optimization problem of the independent variables U and V in Eq. (2) are given by the following Eqs. (4) and (5).

$$v_i = \frac{\sum_{j=1}^{n} u_{ij}^m x_j}{\sum_{j=1}^{n} u_{ij}^m},\ i = 1, 2, \ldots, c \tag{4}$$

$$u_{ij} = \left[\sum_{r=1}^{c} \left(\frac{d_{ij}}{d_{rj}}\right)^{\frac{2}{m-1}}\right]^{-1}\quad i = 1, 2, \ldots, c,\ j = 1, 2, \ldots, n \tag{5}$$

Equations (4) and (5) compose an iterative optimization procedure. The goal of the iterative procedure is to get a sequence of fuzzy clustering centroid until no further improvement in $J_{fcm}(U, V)$ is possible and the gengeral steps of the FCM algorithm are defined as follows:

Step1: Preset a number of clusters c ($1 < c < n$) and a value of the fuzzy exponent m ($1 \leq m < +\infty$), initialize the clustering centroids $V^{(0)}$ set the convergence accuracy $\varepsilon > 0$, set the number of the iteration $k = 0$;

Step2: Use the Eq. (5) to calculate the $U^{(k+1)}$;

Step3: Use the Eq. (4) to calculate the $V^{(k+1)}$ and $k = k + 1$;

Step4: Repeat the Step2 and Step3 until the improvement in $J_{fcm}(U, V)$ is no more than $\|V^{(k)} - V^{(k-1)}\| \leq \varepsilon, k \geq 1$.

In FCM, the sum of membership u_{ij} that x_j belongs to all c classes is one, the membership value of the x_j assigned to jth class is only depend on the sum of the ratio of d_{ij} and d_{rj}, as shown in Eq. (5). So the membership value u_{ij} can't reflect the true distance d_{ij}. This defect caused the FCM sensitive to noise and the initial parameters.

3. The IKDFCM Algorithm

Based on the analysis above, we know that the FCM algorithm assigns membership of x_k is inversely depended on the relative distance of x_k to the cluster centroid V_i in the FCM model. If there are two points (one is noise), they both have the same distance to the two cluster centroid (one short distance is real data point, one long distance is the noise data point), so the memberships of the two points will be the same ($u_{ij} = 0.5$), this makes the FCM algorithm sensitive to the noise. The FCM algorithm uses the iterative gradient descent to accomplish, it is sensitive to the initialization parameters of cluster centroid and the membership matrix, this method can't guarantee converge to the global optimal. To overcome these shortcomings, we proposed a novel clustering model used in radar HRRP target recognition, named IKDFCM.

3.1 The IKDFCM Algorithm

Suppose $X \in R^s$, x_1 and x_2 are s-dimensional vector in R^s space, then the inner product of x_1 and x_2 can be written as $\langle x_1, x_2 \rangle$. Define a mapping from original data space X to the feature space H, $\phi : X \rightarrow H$; $\phi(x) = y$, use the inner product in feature space H, we can define the kernel function as Eq. (6).

$$K(x_1, x_2) = \langle y_1, y_2 \rangle = \langle \phi(x_1), \phi(x_2) \rangle \tag{6}$$

Kernel clustering is just use the kernel distance function to replace the distance function in the FCM model and redefine criterion function. The new criterion function can be rewritten as Eq. (7).

$$\begin{aligned} J_{\text{ikdfcm}}(U, V) &= \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^m \left\| \phi(x_j) - \phi(v_i) \right\|_H^2 \\ &= \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^m (K_{jj} + K(v_i, v_i) - 2 \cdot K(v_i, x_j)) \end{aligned} \tag{7}$$

Where K is the $n \times n$ kernel matrix of the kernel function $K(x, y)$. It can be proved that K is symmetric positive semi-definite (PSD) and meets the Mercer theorem.

$$\begin{aligned} K &= \begin{bmatrix} K(x_1, x_1) & \cdots & K(x_1, x_n) \\ \vdots & \vdots & \vdots \\ K(x_n, x_1) & \cdots & K(x_n, x_n) \end{bmatrix} \\ &= \begin{bmatrix} \langle \phi(x_1), \phi(x_1) \rangle & \cdots & \langle \phi(x_1), \phi(x_n) \rangle \\ \vdots & \vdots & \vdots \\ \langle \phi(x_n), \phi(x_1) \rangle & \cdots & \langle \phi(x_n), \phi(x_n) \rangle \end{bmatrix} \end{aligned} \tag{8}$$

We define the set $Q = (i, j)$, the members (i, j) in set Q satisfies the Eq. (9) under the constraint $1 \le i \le c$, $1 \le j \le n$, and use the KKT condition which makes the Lagrange function obtain the extremum under the variables U and V.

$$K_{jj} + K(v_i, v_i) - 2 \cdot K(v_i, v_j) = 0 \tag{9}$$

The IKDFCM algorithm is obtained by separately minimizing $J_{ikdfcm}(U, V)$ over the variable U and V using Lagrange multipliers. A complete statement of the IKDFM algorithm is given next and included safeguarding in case any squared distance $d_{ij}^2 = \|\phi(x_j) - \phi(v_i)\|_H^2 = 0$. If the set Q is null, we have

$$\begin{aligned} u_{ij} &= \frac{n \cdot (K_{jj} + K(v_i, v_i) - 2 \cdot K(v_i, v_j))^{\frac{1}{1-m}}}{\sum_{r=1}^{c} \sum_{j=1}^{n} (K_{jj} + K(v_r, v_r) - 2 \cdot K(v_r, v_j))^{\frac{1}{1-m}}} \\ &1 \le i \le c, \; 1 \le j \le n \end{aligned} \tag{10}$$

If the set Q is non-null, we have: (1) For any i $(1 \le i \le c)$, there exist j $(1 \le j \le n)$ satisfies the Eq. (9), then the u_{ij} could be any real number under the constraint in Eq. (11) and $u_{ij} = 0$ if $K_{jj} + K(v_i, v_i) - 2 \cdot K(v_i, v_j) \neq 0$.

$$\sum_{j=1}^{n} u_{ij} > 0, \; 1 \le i \le c; \; u_{ij} \ge 0, \; \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij} = n \tag{11}$$

(2) When exist i $(1 \le i \le c)$ for any of j $(1 \le j \le n)$ satisfies the Eq. (12), the u_{ij} could be any real number under the constraint in Eq. (13) and $u_{ij} = 0$ if $K_{jj} + K(v_i, v_i) - 2 \cdot K(v_i, v_j) \neq 0$.

$$K_{jj} + K(v_i, v_i) - 2 \cdot K(v_i, v_j) \neq 0 \tag{12}$$

$$u_{ij} \ge 0, \; \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij} = n. \tag{13}$$

Finally, the clustering centroid V is the solution of the following iterative equation.

$$\sum_{j=1}^{n} \left(\frac{\partial K(v_i, v_i)}{\partial v_i} - 2 \cdot \frac{\partial K(v_i, x_j)}{\partial v_i} \right) \cdot u_{ij}^m = 0, \; 1 \le i \le c \tag{14}$$

In the iterative equations of IKDFCM, we relax the column sum constraint in Eq. (3) to the looser constraint in Eq. (11) from one to n. In other words, each element of the k th column in matrix K could be any number between 0 and 1, as long as one of them is positive at least. We put the steps of the IKDFCM algorithm summarized below.

Step1: Set the parameters of the kernel function $K(x, y)$; set the number of the clusters c; the value of m; the convergence accuracy ε and the number of iterations $k = 0$. Use the FCM algorithm to initialize the clustering centroid matrix $V^{(0)}$.

Step2: Use the Eqs. (10) and (11) to calculate the membership matrix $U^{(k)}$.

Step3: Solve the Eq. (14), whose solution is $V^{(k)}$, for $k = k + 1$.

Step4: If $\|V^{k+1} - V^k\| < \varepsilon$ or exist i $(1 \le i \le c)$ satisfies $\sum_{j=1}^{n} u_{ij} = 0$, then stop. Otherwise go back to step 2.

3.2 The Validity Index

To show the effectiveness of the clustering algorithm, many cluster validity indexes have been proposed. In this paper, we use the well-known validity index V_{FS} proposed by Sugeno and Fukuyama in [27] and V_{PCAES} proposed by Wu and Yang in [28] to compare the clustering validity of the FCM and IKDFCM method. The two validity indexes are defined as follows:

$$\begin{aligned} V_{FS} &= J_{fcm}(U,V) - K_m(U,V) \\ &= \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^{m}\|x_j - x_i\|^2 - \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^{m}\|v_i - \overline{v}\|^2 \end{aligned} \tag{15}$$

Where $\overline{v} = \sum_{j=1}^{n} x_j/n$.

$$V_{PCEAS} = \sum_{i=1}^{c}\sum_{j=1}^{n} \frac{u_{ij}^2}{u_M} - \sum_{i=1}^{c} \exp\left(-\min_{k\neq i}\left\{\|v_i - v_k\|^2\beta_T\right\}\right) \tag{16}$$

Where $u_M = \min\limits_{1\leq i\leq c}\left\{\sum_{j=1}^{n} u_{ij}^2\right\}$, $\beta_T = \frac{\sum_{i=1}^{c}\|v_i-\overline{v}\|^2}{c}$, and $\overline{v} = \sum_{j=1}^{n} x_j/n$. From the defining of the index, it's easy to see that the V_{FS} takes the properties of the membership degree and the data geometric structure into consideration together. Smaller V_{FS} means more compact and better separated clusters. Larger value of V_{PCAES} index implies internal aggregation in each class and well separability between classes.

4. The Experimental Result on the Radar HRRP Target

4.1 Experiment Setting

In the recognition experiment, we use the simulated radar HRRP of three ground targets to evaluate the performance of the proposed algorithm. Depending on the geometric model of the real target, corner reflectors with different positions are utilized as the scattering center models to simulate the target and the SFW radar is used to get the HRRP of the targets. We add noise to the echoes to make the simulated HRRP closer to the radar HRRP in real environment. For the sake of illustrating the target-aspect sensitivity problem, the azimuth of each target is from 0° to 179.5° interval 0.5° and the elevation angle constantly is 30°. Thus, each target is comprised of 360 HRRP samples and each sample is a 256-dimensional vector because of the HRRP with size of 256-point. The testing process is mainly divided into three steps: pre-processing phase, training phase and test phase. In the preprocessing phase, HRRP alignment with target geometric center and L_2 normalization are applied to overcome time-shift sensitivity and amplitude-scale sensitivity at first. In order to reduce the computation burden, the KPCA method in [15] is utilized to achieve dimensionality reduction.

To show the effectiveness of the proposed method, we compare the IKDFCM with the fuzzy c-means method (FCM), k-nearest neighbor (K-NN) [26] and the template matching method under the maximum correlation coefficient (MCC-TMM) [9]. TMM is a fundamental method in HRRP recognition. The MCC-TMM utilizes the correlation coefficient between testing samples and the template as the matching score; four samples with nearest azimuth are averaged as a template for MCC-TMM. For all the four methods, we set the nearest neighbor $k = 5$ and choose j ($j = 30, 60, \ldots, 180$) labeled samples equally interval from each target HRRPs as the training set, however, the 180 test samples are randomly selected from the rest samples. All experiments are performed for 100 times so as to get the average result as the recognition accuracy.

4.2 Recognition Result Analysis

We get the average recognition rate versus the number of training samples is presented in Fig. 3 and the average confusion matrix is shown in Table 1 with 180 training samples and SNR = 35dB. From the Fig. 3, we can see that, firstly, the IKDFCM outperforms the other three over all the test number of training samples. When the training samples are fewer than 80, the performance of all methods is poor. Secondly, the recognition rates rise along with the increasing number of training samples, which means all the methods need a bigger training set to achieve a good recognition accuracy. Besides, after the training samples more than 90, the recognition rates of the other three methods rise sharply, but the IKDFCM method rises sharply after the training samples more than 70. That is to say, our method can achieve the same recognition accuracy with fewer training samples. Finally, the performance of MCC-TMM catches up with and surpasses both the FCM and K-NN after the training samples more than 110, which means MCC-TMM needs many of templates to obtain a good performance.

Table 1 shows the confusion matrix and Table 2 shows the average recognition rate and standard deviations of the four methods with 180 training samples at SNR = 35dB. It is easy to see that the performance of IKDFCM is the best, MCC-TMM is the next one, the average recognition rate of which is approximately 2.7 percentage point higher than K-NN, the FCM is the last one. The standard deviation of the IKDFCM is slightly larger than the MCC-TMM. By analyzing the theories and experimental results, we can easily find that the method, which only considers the distance between the clustering centroid and the test samples but ignore the samples' inner structure information, cannot achieve good recognition accuracy. The FCM and K-NN obey the assumption that the neighboring samples have the

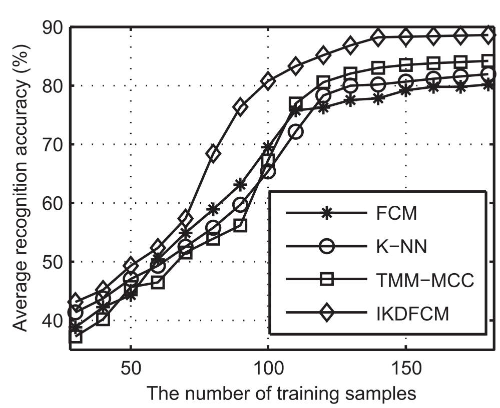

Fig. 3 The recognition rate versus the number of training samples when SNR = 35dB.

Table 1 The confusion matrix and the average recognition rates on HRRP with 180 training samples and SNR = 35dB.

	FCM			K-NN			MCC-TMM			IKDFCM		
Target	BMP2	T72	BTR70	BMP2	T72	BTR70	BMP2	T72	BTR70	BMP2	T72	BTR70
BMP2	148.77	33.55	16.2	149.89	18.62	15.9	157.88	25.31	11.26	163.21	18.16	10.21
T72	15.11	130	9.8	17.44	137.68	10.94	9.27	144.68	16.15	3.89	152.46	7.29
BTR70	16.12	16.45	154	12.66	23.7	153.16	12.85	10.01	152.59	12.90	9.38	162.5
accuracy (%)	82.65	72.22	85.55	83.27	76.49	85.09	87.71	81.38	84.77	90.67	84.7	90.28

Table 2 Average recognition rate and standard deviations.

	FCM	K-NN	MCC-TMM	IKDFCM
mean	80.14	81.95	80.14	88.55
std	5.72	6.39	2.58	2.73

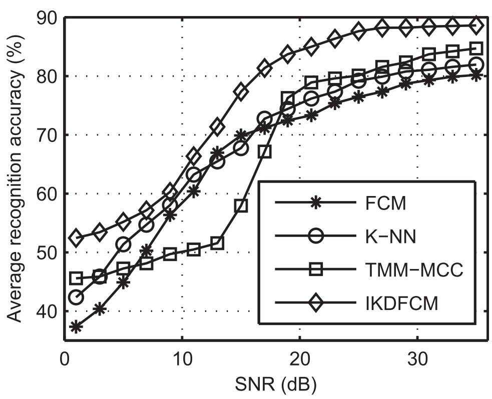

Fig. 4 The average recognition rate versus the SNR (the training samples are 180).

same label, so they can't find the underlying structure information hiding in the samples. The IKDFCM use the kernel function to map the HRRP from original low-dimensional space to high-dimensional feature space. It has the ability to find inner structure information hides in the HRRP, which is depending on the structure of the target and not be affected by the target-aspect variation.

According to the introduction in Sect. 1, there always exists noise in the radar echoes. And, we add noise in the echoes so as to be closer to the true target environment. For ground targets we assumed the noise in the inphase and quadrature echoes of targets to be Gaussian white noise. The average recognition rates of the four methods versus SNR are shown in Fig. 4. The figure shows that, for all the methods, the recognition performance improves along with the increasing of the SNR, the recognition rate of the IKDFCM remains stable after the SNR higher than 25dB and the threshold of the others is 30dB, then a very rapid deterioration of the recognition rate can be observed after the SNR under 20dB. The relatively high accuracy at high SNR can be partly explained by the fact that the HRRP is a combination of smaller magnitude and larger magnitude scatters that determined the recognition rate. The smaller magnitude scatters are more likely to be affected by the increasing noise, which corrupts the inward structure of HRRP and quickly have an impact on reducing the recognition rate. Obviously, the FCM is most sensitive to noise and the IKDFCM performs the best. Compared with the FCM, in the step 1 of IKDFCM algorithm, we relax the column sum constraint in Eq. (3) from one to n, in other words, each membership value u_{ij} can be any number between 0 and 1. This change improves the anti-noise performance and the robustness of the original algorithm, therefore, the IKDFCM can obtains better recognition rate than the other methods under the same SNR.

Table 3 Summary of selected UCI data sets.

Dataset	Instance	Class	Attribute
Annealing	798	6	38
Chess	3196	2	36
Redwine	1599	6	11
Yeast	1484	10	8

Table 4 The average classification accuracy (%) on four various UCI datasets using four different algorithms.

	FCM	K-NN	MCC-TMM	IKDFCM
Annealing	72.08	71.52	77.08	80.82
Chess	72.34	76.38	75.56	81.66
Redwine	75.67	72.84	77.92	79.39
Yeast	74.92	67.42	77.49	77.54

To further assess the performance of the proposed method, the real data sets in Table 3 are used to carry out our experiments, which are from the UCI machine learning repository [34]. Since no test sets are included in the Annealing, Chess, Redwine and Yeast datasets, 5-fold cross-validation is used to evaluate the accuracy of the above four methods. That just says, each dataset is randomly split into five folds, each of which is tested with the remaining four as training set. The classification accuracy is regarded as the performance measure.

In Table 4 the average results based on the four datasets are shown. We can see that the classification accuracy of the proposed method is preferable than the other methods in all the test datasets. In Yeast dataset, the classification accuracy is slightly, 0.05%, higher than the MCC-TMM method, the possible reason is the performance affected by number of the attribute, which is 8 in Yeast dataset, lower than the three others 38, 36, 11. Owing to this, the performance of IKDFCM become worse. In other datasets, the advantage is obvious. Comparing Table 2 with Table 4, we find that the best accuracy based on the true datasets is lower than the simulated HRRP data, the result in line with common sense of the algorithms.

Table 5 The validity index and recognition rates of FCM and IKDFCM.

	V_{FS}	V_{PCAES}	Accuracy (%)
FCM	0.48	3.27	80.14
IKDFCM	0.41	3.89	88.55

Table 6 The time costs of the four methods on the test set.

algorithm	elapsed time (ms)
FCM	21.1ms
K-NN	17.8ms
MCC-TMM	50.3ms
IKDFCM	22.6ms

4.3 Validity and Complexity Analysis

As the K-NN and MCC-TMM don't have the validity index of clustering, we just compare the validity index of the FCM and IKDFCM. First initialize the parameters in the kernel function and set the fuzzy exponent $m = 2$, the convergence accuracy $\varepsilon = 0.001$, FCM runs for a maximum of 100 interactions. The result is shown in Table 5. It shows that the IKDFCM algorithm outperforms the FCM algorithm with smaller value of V_{FS} index and larger value of V_{PCAES} index. Through the analysis of the clustering validity index in Sect. 3.2, we can get the conclusion that IKDFCM is more accurate than the FCM in terms of clustering accuracy and validity for radar HRRP target. For a recognition system, the computation cost in the training phase can be expected to be completed in advance, we should only evaluate the method's computation cost in the testing phase. It is difficult to evaluate the difference of these computation costs in quantity; we just give the cost of time to classify a HRRP test sample by the four algorithms under completely the identical experiment condition. The configuration of the computer is 8 cores; frequency of each core is 3.2GHz; memory is 16G. We analyze the average results of all methods after executing 100 times and all the parameters are set to be the same as the experiments above. The result is shown in Table 6. Obviously, from the average running time, the fastest K-NN just uses about 17.8ms. The FCM and IKDFCM are the succeeding; the MCC-TMM uses 50.3ms in the last. Comparing to the 21.1ms of FCM method, our method just uses a little more than it, however, our method gets the higher accuracy. Taking all sides into consideration, the proposed method has relatively low computation complexity and better performance of HRRP recognition.

5. Conclusions

In this paper, based on the FCM, we proposed an improved algorithm, called IKDFCM, to recognize the radar HRRP target. We introduce the kernel function to replace the distance function and relax the column sum constraint of the membership matrix in the FCM. Then we evaluate the performance of the proposed method with three additional contrast algorithms on three radar HRRP targets and four UCI datasets. All the experiments result show that the IKDFCM method not only has a better recognition performance than the other three, but also better robustness and lower time complexity and space complexity. Further research is to study the influence of different kernel functions and distance functions on radar HRRP target recognition accuracy.

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